Cryptorcurrency returns: short-term forecast using Google Trends

Master's Thesis submitted

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Abstract

Uncertainty about intrinsic value of cryptocurrencies and proven impact of attention on market value of various assets motivated us to investigate an impact of attention on cryptocurrencies' market value. As an attention indicator, we employed Google search volume data based on keywords related to our set of cryptocurrencies of a minute granularity. Using ARMA and VECM, we tested, whether Google search volume improves prediction for cryptocurrencies' price development in timeframe from 15 minutes to a day. Subsequently, we simulated trading using this out-of-sample forecast and came to conclusion, that in case of frequent trading with no fees, simple univariate autoregressive models are performing better. However, when fees are not omitted, inclusion of Google search volume variable improves trading results, especially in case of hourly and daily frequencies. Under such frequencies, it outperformed univariate models as well as the growth of the underlying assets.

Keywords: Google Trends, Cryptocurrency, Search Volume, Granularity, Trading, VECM

The complete R and Python code used in this thesis is available on Github [1]

[1] https://github.com/pulecvoj/thesis-google-crypto-trading

Contents

List of Abbreviations

ADF	augmented Dickey–Fuller
AIC	Akaike information criterion
API	application programming interface
ARCH	autoregressive conditional heteroscedastic
ARIMA	autoregressive integrated moving average
ARMA	autoregressive–moving-average
BIC	Bayesian information criterion
CRIX	CRyptocurrency IndeX
ETH	Ethereum
EUR	Euro
HQC	Hannan–Quinn information criterion
IMRAD	Introduction, Methods, Results and Discussion
KPSS	Kwiatkowski–Phillips–Schmidt–Shin
LTC	Litecoin
MDA	mean directional accuracy
MSE	mean squared error
OLS	ordinary least squares
SVI	search volume index
USA	United States of America
UTC	Coordinated Universal Time
VAR	vector autoregression
VECM	vector error correction model
XBT	Bitcoin
XMR	Monero

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1 Introduction

The first decade of the 21^{st} century witnessed an emergence and rise of two strong phenomena – Google and Bitcoin. Google, since its foundation in 1998, managed to establish itself as a leading search engine worldwide. Even though different sources show a variation in perceived Google market share, none of them doubts its dominance. Since 2006, there was a possibility to get a search volume data from Google via Google Trends, however it was rather limited compared to nowadays, due to the fact, that it required regular updates executed by Google. Moreover, it provided only simple data on search usage (Jun et al., 2018). A major breakthrough happened on 6^{th} of August 2008 when a free service Insights for Search was launched which enabled downloading statistics of search volumes via its interface. Currently, the service Insights for Search is merged with Google Trends. Its launch was covered by press, for example an article, written by Schwartz (2008), provided even a short go-through of its functionalities at that time. Overall, this event significantly broadened the accessibility of search data for research purposes and ignited its usage in academia. Even prior to Google Trends we can find studies using web-based search data, for example one by Ettredge et al. (2005), but the authors faced limitations in obtaining the data. After 2008 we can observe a boom in scientific works using this type of data in diverse fields, which are sampled and analysed in "Ten years of research change using Google Trends: From the perspective of big data utilizations and applications" by Jun et al. (2018). According to the same authors and general consensus, the first paper demonstrating usefulness of search queries for predicting is "Detecting influenza epidemics using search engine query data" by Ginsberg et al. (2009), where they managed to forecast a spread of influenza earlier than national public health authority (Centers for Disease Control and Prevention). Naturally, emerged the question, since Google searches are capable to predict influenza outbreak, what else are they capable to predict? The area for application of Google Trends-based forecasting and nowcasting is broadening constantly. For instance, it is used to estimate economic indicators such as car sales or consumer confidence by Choi and Varian (2012), unemployment by Pécsyová (2011) and Pavlicek and Kristoufek (2015), mortgage credit demand and housing market by Mclaren and Shanbhogue (2011) and Saxa (2014), tourist volumes by Yang et al. (2015) or issues salience in sociology by Mellon (2013).

Not long after Insights for Search another strong phenomena emerged. A Bitcoin ledger based on white paper by Nakamoto (2008) was launched on 3^{rd} of January 2009, setting up Bitcoin and starting the era of cryptocurrencies. Cryptocurrency is purely virtual asset, is traded almost exclusively online and has not-easy-to-measure intrinsic value, therefore the drivers of cryptocurrency value are popular topic among researchers.

Since we may consider attention as a scare resource from Kahneman (1973) and it was demonstrated, that attention improves assets' performance on stock market as stated by Da et al. (2009), we might ask whether this works also for cryptocurrencies. This question has been answered partially by Kristoufek (2013), who identified a positive impact of Google search volume on Bitcoin price. However, this analysis has been performed only on weekly data for a long-term relationship, whereas our goal is to investigate, if the same applies in a short-term dynamics.

The hypothesis we would like to test is whether an inclusion of Google search volume, represented by Search Volume Index (SVI), could improve quality of short-term forecasting and trading based on this forecasting. The logic behind is relatively simple – we believe that there are at least some people, who are trading crytpocurrencies and who are looking for news before trading, implying they would type regularly specific keywords into Google. In other words, their interaction with search engine precedes their interaction with the market and this gap could be utilized for short-term forecasting of market development. To support a necessity of testing given hypothesis, we might consider development of SVI and cryptocurrecy price presented in Figure 1, which shows significant co-movements visible even by naked eye.

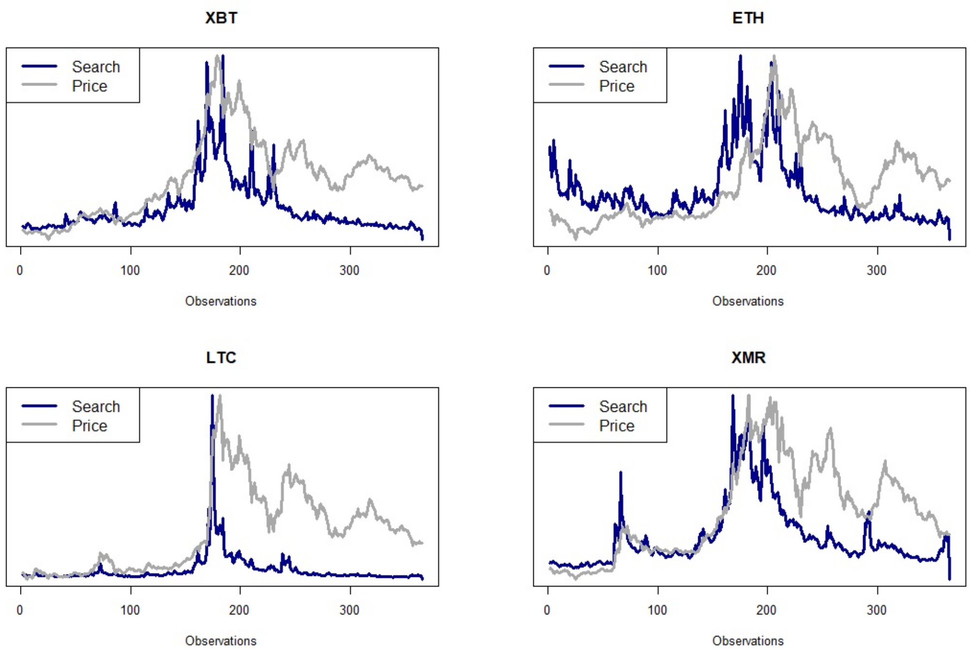

Figure 1.1: Development of SVI and cryptocurrencies' prices, zoomed in with various scales

Especially the research in a field of attention trading became a hot topic. In 2013, The Wall Street Journal published an article "How Gangnam Style Drove an 800% Stock Rise" showing that a value of company owned by father of successful singer Psy, whose business is manufacturing semiconductor testing equipment and thus unrelated to entertainment industry, rose by 800% without any relevant reason (Jun, 2013). However, this anecdotal evidence is supported by academic research. Fink and Johann (2014) utilized Google daily search volumes and found, "...that daily changes in the Google Search Volume Index are related to liquidity in its different dimensions" and "...that high attention triggers positive short term returns" on German stock market. Nevertheless, the analyses of other stock markets confirmed these conclusion only partially. They agree on increase in volatility. On the contrary, they do not see increase in short-term returns but rather a decrease in long-term returns as stated by Bijl et al. (2016) and Kim et al. (2018), whose results contradict Kristoufek (2013) findings about Bitcoin. Even though there is consensus among researchers on relevance of Google search volume for predicting future, there is no clear consensus about the impact of Google search volume on returns.

Compared to the aforementioned papers, our research provides an additional value through its finer granularity and robustness of analysis. For our analysis, we utilize finest data possible - minutely data from Google and trade-by-trade for cryptocurrencies. Most of the researchers used weekly or daily data at best as the standard Google Trends interface does not enable downloading neither finer granularities for historical period nor larger datasets at once. Consequently, the past research focused on relatively long-term relationship, whereas we have the advantage of investigating the very short-term one. To our knowledge, we are the first utilizing such long period of high frequency Google search data. For performing such analysis, we adopt an approach composing of three major workstreams.

The first step is to obtain the data of necessary quality, which required a usage of pseudo API in Python and standard API in R over multiple days and IP addresses, because all the data sources limit the frequency and the total number of data requests per day, while we have literally tens of thousands of data requests. As a result we employ one year data for four cryptocurrencies - Bitcoin, Ethereum, Litecoin and Monero.

The second step is to fit the statistical models. We compare univariate model against models incorporating SVI in different manners. Specifically, as univariate model we employ ARMA and ARIMA and as multivariate we use VAR and VECM. We do so for different cryptocurrencies and granularities ranging from 15 minutes up to one day. In addition, we use multiple lengths of learning period for each granularity in order to investigate, how many past observations are optimal to train our models. In total, we have four cryptocurrencies, four granularities, four learning periods for each granularity and we are fitting four different models implying we fit 4^4 models (i.e. 256).

The last step is to simulate trading utilizing models from the step two. We are performing trading based on directional prediction of every single one out of our 256 models in three different scenarios, meaning we have 768 difference performances to evaluate.

Once we perform above-mentioned steps, we may draw a conclusion. Overall, we cannot recommend usage of Google Trends as universal tool for improving short-term prediction of cryptocurrency market, but we can suggest its usage as tool for improving prediction and upon that based trading in case of hourly to daily predictions. Also, we would like to stress, that achieved improvement varies over the different cryptocurrencies.

In this paper we follow IMRAD method (Introduction, Methods, Results and Discussion). In this section we covered motivation and hypothesis of the paper, review of existing literature and high-level description of approach for testing our hypothesis. The Section 2 is methodological section, where we in detail discuss approach for data processing and analysis, including specification of employed statistical models. Section 3 is data section, where we describe which data we use, how we collected them and show their key statistical properties. In Section 4, we provide and explain aggregated results and answer questions raised by our hypothesis. In Section 5, we provide a conclusion and a brief summary of the work done and key results. We also pinpoint limitations of our research and outline topics for further research. In the end of the thesis we provide an appendix, where detailed results and additional illustrations are presented.

2 Methodology

We follow standard approach for univariate and multivariate time series analysis as is described in books focused on time series analysis and financial econometrics such as Tsay (2006), Lütkepohl (2007) or Brooks (2008). We perform series of statistical tests verifying applicability of selected models. After that, for univariate analysis, we use family of ARMA models and for multivariate we use VAR model or VECM.

2.1 Statistical tests

Prior to model application, we have to verify, whether the time series are stationary. For doing so, we use the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test from Kwiatkowski et al. (1992) and the augmented Dickey-Fuller (ADF) test by Said and Dickey (1984). The reason for using both of them is opposite null hypothesis (H_0), where KPSS's H_0 assumes stationarity, while ADF's H_0 assumes a presence of unit root.

Furthermore, we need to check whether autocorrelation is present for our time series. Application of autoregressive model for stationary series with no autocorrelation is not particularly useful. The testing is done by performing Ljung–Box test by Ljung and Box (1978), which assumes data being independently distributed under H_0 .

In case of multivariate analysis, we need to control for potential cointegration of time series. In order to reject such relationship or to identify number of a cointegration vectors, we apply both versions of Johansen test from Johansen (1991), namely "trace" and "eigenvalue".

To preliminary answer the question about explanatory power of time series, we test for the Granger causality as defined by Granger (1969). Since we use the function "grangertest" from R package "lmtest", we technically perform Wald test where we compare explanatory power of restricted and unrestricted models. In the restricted model, the explained variable is regressed only on its own lags while in the unrestricted model, the explained variable is regressed on its own lags and lags of other potential explanatory variable. We perform the test for Granger causality for all the explanatory variables, namely various differentiation of search volume by assumed attention, as described in detail in Section 2.5.

We also test residuals of the models in order to reject an inappropriately chosen model. Namely, we test residuals for non-zero mean by t-test, presence of heteroscedasticity and autocorrelation between residuals by Ljung-Box test and normality of residuals by using Shapiro-Wilk test by Shapiro and Wilk (1965) and Lilliefors test by Lilliefors (1967).

2.2 Univariate analysis

For univariate analysis we use ARMA model (2.1):

$$r_t = \alpha + \sum_{i=1}^{p} \phi_i r_{t-i} + \epsilon_t + \sum_{i=1}^{q} \theta_i \epsilon_{t-i} \tag{2.1}$$

where $\{r_t\}$ stands for a series of cryptocurrency log returns, $\{\epsilon_t\}$ stands for white noise series of error term, α is a constant which takes non-zero values in case of non-zero mean of $\{r_t\}$, and p and q are non-zero integers specifying the number of selected lags. For model specification, we use standard Box-Jenkins approach by Box and Jenkins (1976).

First, we check whether the time series is stationary by above mentioned KPSS and ADF tests. If not, we perform the first differentiation. Thus, instead of cryptocurrency price we use its returns as suggested in the model description. In some cases this might not be enough, therefore, we proceed to use log-differentiation or, in other words, log returns.

Thereafter, we check whether the time series is showing any signs of seasonal patterns. It is useful to observe development of autocorrelation over time or employ a spectral plot by Jenkins and Watts (1968). Since we use rolling window approach (described in Section 2.4) with relatively short learning period for returns of asset traded globally and continuously, seasonality is unlikely to be relevant. Situation might be different for traded volume, where daytime would play a role, i.e. day/night in main market-driving countries such as China and USA suggested by Hileman and Rauchs (2017), Ibinex (2018) or Kristoufek (2015). However, investigating traded volume is not within the scope of our work.

We identify lag order of p for autoregressive process and q for moving average process by fitting different lags combination and comparing AIC (Akaike information criterion) from Akaike (1974), BIC (Bayesian information criterion) from Schwarz (1978) and HQC (Hannan-Quinn information criterion) from Hannan and Quinn (1979) of such models. Since we literally perform hundreds of thousands of model estimation, we need to automate that process. In our case, we rely on function "auto.arima" from package "forecast". This function also enables to fit ARIMA, in case our log-differenced series would not be stationary on small subsample that is relevant for current model fitting. However, this is unlikely in practice.

For each model fitting, we perform residuals check in order to assess how trustworthy the fit actually is. As mentioned in Section 2.1, we test the absence of non-zero mean, heteroscedasticity, autocorrelation, normality and presence of ARCH effects from Engle (1982).

2.3 Multivariate analysis

In this section, we enrich our univariate model by other explanatory variable which is time series of Google search volume obtained from Google Trends. We label it $\{svi_t\}$ which stands for log-differenced Search Volume Index (SVI).

2.3.1 VAR models

As the first multivariate model, defined by equations (2.2) and (2.3), we use Vector autoregression of order p (VAR(p)) with Search Volume Index which we define as follows:

$$r_t = \alpha_1 + \sum_{i=1}^{p} \beta_{1,t-i} r_{t-i} + \sum_{i=1}^{p} \gamma_{1,t-i} svi_{t-i} + \epsilon_{1,t} \tag{2.2}$$

$$svi_t = \alpha_2 + \sum_{i=1}^{p} \beta_{2,t-i} r_{t-i} + \sum_{i=1}^{p} \gamma_{2,t-i} svi_{t-i} + \epsilon_{2,t} \tag{2.3}$$

where series of $\{r_t\}$ and $\{svi_t\}$ are stationary, α is a constant and ϵ_t is a sequence of serially uncorrelated random vectors with zero mean.

The second multivariate model, equations (2.4) and (2.5), includes dummy variable for the case when searches are driven by positive attention (more about identification attention is in Section 2.5). The goal is to differentiate between search volume impact and search volume impact when the market mood is perceived as positive. We define the model as follows:

$$r_t = \alpha_1 + \sum_{i=1}^{p} \beta_{1,t-i} r_{t-i} + \sum_{i=1}^{p} \gamma_{1,t-i} svi_{t-i} + \sum_{i=1}^{p} (\phi_{1,t-i} svi_{t-i} + \zeta_{1,t-i}) D_{t-1}^{+} + \epsilon_{1,t} \tag{2.4}$$

$$svi_t = \alpha_2 + \sum_{i=1}^{p} \beta_{2,t-i} r_{t-i} + \sum_{i=1}^{p} \gamma_{2,t-i} svi_{t-i} + \sum_{i=1}^{p} (\phi_{2,t-i} svi_{t-i} + \zeta_{2,t-i}) D_{t-1}^{+} + \epsilon_{2,t} \tag{2.5}$$

The addition to the first model is $\{D_t^+\}$ series which is binary series indicating whether the market mood is positive and thus so is the attention. This enables us to see, whether there is an extra effect of positivity of motivation behind search volume expressed by the term $\{D_t^+\} * \{svi_t\}$ as well as whether there is general push by the positive mood on the market expressed by the dummy variable itself.

The third multivariate model, equations (2.6) and (2.7), adds another dummy variable for the case when the searches are driven by negative attention. The default situation is when attention is driven by mixed mood and to account for that we add two dummy variables for positive and negative mood, suggesting we consider three moods: negative, mixed and positive (more about mood identification in Section 2.5). Therefore, this model enables us to identify search volume impact when market mood is mixed, impact when the market mood is perceived as positive, and search volume impact when the market mood is perceived as negative. We define the model as follows:

$$\begin{aligned}
r_t &= \alpha_1 + \sum_{i=1}^{p} \beta_{1,t-i} r_{t-i} + \sum_{i=1}^{p} \gamma_{1,t-i} svi_{t-i} + \sum_{i=1}^{p} (\phi_{1,t-i} svi_{t-i} + \zeta_{1,t-i}) D^{+}_{t-1} + \\
&\quad + \sum_{i=1}^{p} (\theta_{1,t-i} svi_{t-i} + \eta_{1,t-i}) D^{-}_{t-1} + \epsilon_{1,t} \qquad (2.6) \\
svi_t &= \alpha_2 + \sum_{i=1}^{p} \beta_{2,t-i} r_{t-i} + \sum_{i=1}^{p} \gamma_{2,t-i} svi_{t-i} + \sum_{i=1}^{p} (\phi_{2,t-i} svi_{t-i} + \zeta_{2,t-i}) D^{+}_{t-1} + \\
&\quad + \sum_{i=1}^{p} (\theta_{2,t-i} svi_{t-i} + \eta_{2,t-i}) D^{-}_{t-1} + \epsilon_{2,t} \qquad (2.7)
\end{aligned}$$

The addition to the second model is $\{D^{-}_t\}$ series which is a binary series indicating whether the market mood was negative and thus so was the attention. This enables us to see whether there is extra effect of negativity of motivation behind search volume.

2.3.2 VECM

As we discussed in Section 2.1, we consider potential cointegration of our time series. We follow Engle and Granger (1987) and Lütkepohl (2007) and since our original time series $\{r_t\}$ and $\{svi_t\}$ are non-stationary (before log-differencing), we also check whether their linear combination $\{u_t\}$, defined by equation (2.8), is stationary:

$$r_t - \beta svi_t = u_t \qquad (2.8)$$

assuming we can estimate $\{u_t\}$ by OLS where $\{\hat{u}_t\}$ stands for the deterministic term. We first estimate error correcting term $\{\hat{u}_t\}$ by OLS and then plug it into VAR representation, we get:

$$\hat{u}_t = r_t - \alpha - \beta svi_t \qquad (2.9)$$

and consequently

$$r_t = \alpha_1 + \sum_{i=1}^{q} \beta_{1,t-i} r_{t-i} + \sum_{i=1}^{q} \gamma_{1,t-i} svi_{t-i} + \kappa_1 \hat{u}_{t-1} + \epsilon_{1,t} \qquad (2.10)$$

$$svi_t = \alpha_2 + \sum_{i=1}^{q} \beta_{2,t-i} r_{t-i} + \sum_{i=1}^{q} \gamma_{2,t-i} svi_{t-i} + \kappa_2 \hat{u}_{t-1} + \epsilon_{2,t} \qquad (2.11)$$

We add error-correcting term in the same manner for other variations of VAR(p) model, namely equations (2.4), (2.5), (2.6) and (2.7). By doing so, we get vector error correction model of order q (VECM(q)) which we use in case when cointegration is present.

For estimating both VAR and VECM models, we again automatize lag selection. In this case, we employ function "VARselect" from package "vars" which assess optimal number of lags based on AIC, BIC and HQC criteria. Similarly as for univariate approach, for each model fitting we perform residuals check in order to assess how trustworthy the fit actually is. As mentioned in Section 2.1 we test for absence of non-zero mean, heteroscedasticity, autocorrelation, normality and presence of ARCH effects.

2.4 Model parameters, implementation and results comparison

This section clarifies how we implement and evaluate performance of models mentioned in Sections 2.2 and 2.3.

2.4.1 Model fitting

The sample, to which we are fitting the models, is a set of one year time series. Their granularity is one minute or one trade (more information about data structure is in Section 3). It implies three key features:

- Granularity – we fit the model on a data sets of different granularity, ranging from 15 minutes up to a day. That brings us different amount of observations over the same time period. To obtain coarser granularities we either take weighted average in case of prices or we take sum in case of volumes.
- Learning period – length of the sample in which we fit our models to get coefficient for the prediction. The length depends on granularity and is done to meet "natural milestones" such as learning on past half-day, past day or past week. For each granularity, we use four different lengths of learning period. Table 2.1 shows all the combination of granularities and learning periods.
- Rolling window – we fit the model only for small subset of the sample, which has the length of learning period, and then we fit it again for overlapping window with shift of one unit of the granularity.

Period / Granularity	1/2 day	1 day	2 days	3 days	4 days	1 week	2 weeks	3 weeks	4 weeks	6 weeks
15 minutes	X	X		X		X				
30 minutes		X		X		X	X			
1 hour			X		X	X	X			
1 day							X	X	X	X

Table 2.1: Employed learning periods for given granularities

2.4.2 Forecasting and results comparison

Using a rolling window for model fitting leads to out-of-sample forecast (since it assumes having enough data out of training set). This is true in our case, since training set is only a small fraction of the whole sample. Thus, we perform an out-of-sample forecast for n steps ahead, where n always takes value of $1, 3, 5, 10$ and 15 regardless the granularity of data. Therefore, with 15 minute granularity, we forecast 15 minutes, 45 minutes, 1.25 hour, 2.5 hour and 3.75 hour ahead, while with day granularity, we forecast $1, 3, 5, 10$ and 15 days ahead. Hence, the most important for us is 1-step ahead since we use this prediction as an input for our trading simulation.

To evaluate a quality of the forecast, we utilise two different metrics. One is Mean Directional Accuracy (MDA) which tells us how good the model is in predicting whether the market will go up or down. MDA is defined:

$$MDA = \frac{1}{N} \sum_{t}^{N} \mathbb{1}_{[sign(r_t)==sign(\hat{r}_t)]} \tag{2.12}$$

where N is total number of forecasts made, $\mathbb{1}$ is indicator function, that returns 1, if condition is met and 0 otherwise, r_t is the actual return in period t and $\hat{r}_t$ is the forecasted return for the same period. The other one is a Mean Squared Error (MSE) which measures how much wrong the model was but irrespective of the direction. MSE is defined:

$$MSE = \frac{1}{N} \sum_{t}^{N} (r_t - \hat{r}_t)^2 \tag{2.13}$$

where N is total number of forecasts made, r_t is the actual return in period t and $\hat{r}_t$ is the forecasted return for the same period.

2.4.3 Trading simulation

After measuring quality of forecasts, we are also interested in how would trading based on these different forecasts perform. To compare the performance we simulate trading that is done solely based on predictions of all models mentioned above. Figure 2.1 illustrates how the decision – sell, buy or hold – is created. By sell we understand exchanging our whole cryptocurrency holding into Euro at the current market spot price at time t. By buy we understand exchanging our whole Euro holding into cryptocurrency at the current market spot price at time t. By hold, we understand no change irrespective whether we currently posses Euro or cryptocurrency.

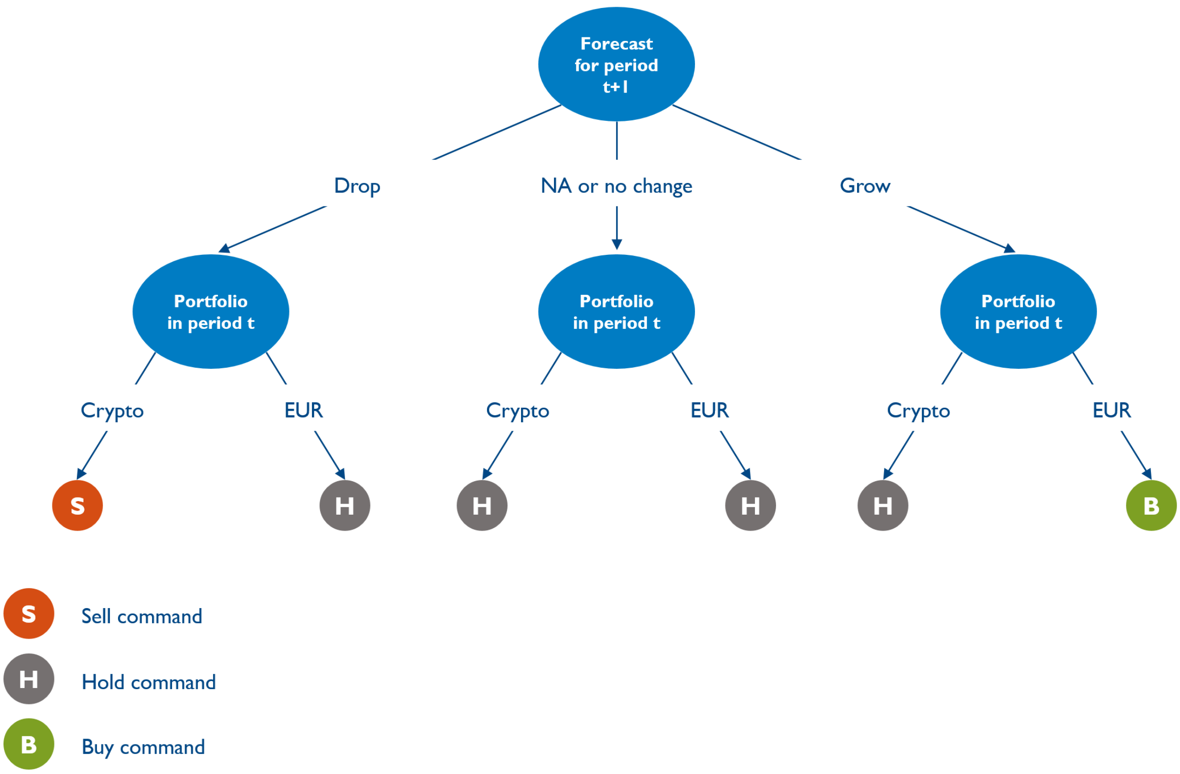

Figure 2.1: Sell/hold/buy decision tree for period t

As illustrated by Figure 2.1 decisions can lead only to three outcomes. Consequently, Figure 2.2 illustrates how decisions over multiple points of time influence our portfolio. The decision thus takes into account our current position and forecast for the next period.

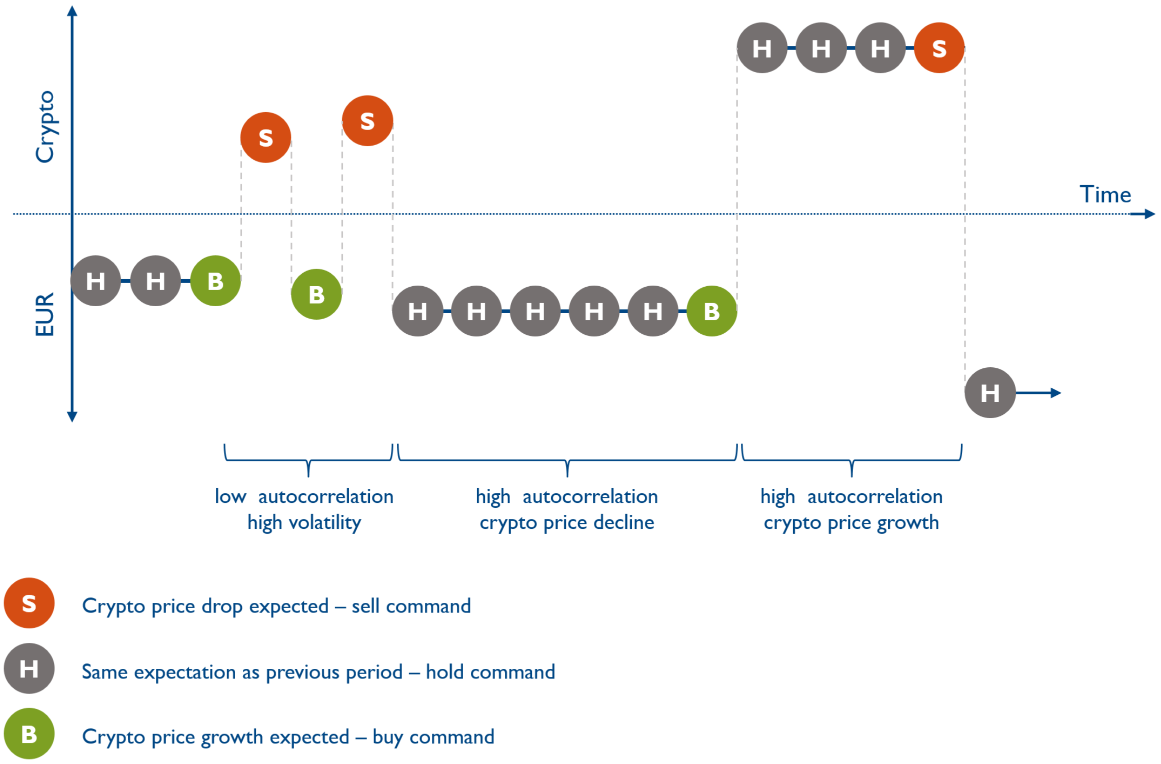

Figure 2.2: Portfolio position development

As illustrated by Figure 2.2, our portfolio has only two positions, either we are completely in cryptocurrency or we are completely in Euro. To measure performance of different forecasts, we compare returns achieved over same period of time. That enables us to see which model performed the best in general and which model performed the best under specific market conditions.

We compare the models over granularities utilised and corresponding learning periods. Besides theoretical comparison assuming frictionless market with no fees, to simulate the real world, we include fees per transaction. These fees are actual fees from Kraken exchange, namely 0.26% as highest taker fee and 0.1% as lowest taker fee. These taker fees are applicable to market participant buying/selling at spot price in time t, therefore we pay them for every transaction we make. Hence, finer granularities are expected to reach better absolute gains when fees are omitted, but inclusion of fees would penalize finer granularities for too high trading frequency. We consider only taker fees since we decide sell/hold/buy, but do not specify the price and thus take the current market price. More information about fee structure is available at *www.kraken.com/help/fees*. Furthermore, we assume no liquidity constraints at the market and we consider Euro having zero gain or loss in its value over our period.

To evaluate performance of simulated trading, we simply take the ratio of money we have at the start and money we have at the end, one year later:

$$performance = \frac{EUR_{end}}{EUR_{beginning}} \tag{2.14}$$

In reality, to optimize model performance for each of granularity or learning period, we would need to consider trade-off between gain and fee per transaction. However, in our simple decision tree we do not consider it and we trade as there were no fees.

2.5 Positive and negative attention identification

For the multivariate models mentioned in Section 2.3, we use not only SVI, but also motivation behind the search whether it was positive or negative. For the purpose of this analysis, we use relatively simplistic approach where we focus at past market performance which is expressed by CRyptocurrency IndeX (CRIX) and based on it, we assume the overall market mood. We employ two types of differentiating SVI, one we call "binary" and the other "quartiles". They are defined as follows.

Binary - we recognize only positive and negative attention driven market mood. Mood is perceived as positive, if the overall return between now and 24 hours ago is positive. In case of coarser granularity, more than 1 hour, we base the mood on overall return between now and 168 hours ago, sticking again to "natural milestones".

Quartiles - we recognize positive, negative and mixed attention. First, we calculate all returns for respective time windows (24 hours and 168 hours). As the next step, we sort the returns from the whole sample and periods associated with returns in lower quartile we consider as periods with negative mood. Analogically, periods associated with returns in upper quartile we consider as periods with positive mood. Periods associated with returns in two middle quartiles we consider as periods with mixed mood.

More sophisticated approach is taken by Nasekin and Chen (2018), where sentiment analysis on social network posts is done, namely StockTwits. Using vector of sentiment would be an interesting approach in further research to identify more accurately sentiment of the attention.

3 Data

In the thesis we utilize three main sources of data. First are prices of selected cryptocurrencies, second one is the SVI from Google Trends for same currencies and last one is CRyptocurrency IndeX. This section focuses on the sources, collection method and statistical description of the data samples.

3.1 General characteristics

Since the three data sources are jointly used for analysing cryptocurrencies' market, they need to share basic properties:

- Time frame – our time series start after midnight on 21^{st} of June 2017 and end on midnight 21^{st} of June 2018. This period covers the boom and bust of the crypto market, where the peak is almost in the middle of the sample. For Bitcoin (XBT), as a leading currency, we have seen prices starting from $2,419$ XBT/EUR going through $16,308$ as well as $1,614$ to ending at $5,798$, thus we have observed turbulent period. Even though we have entire period in minute granularity, cryptocurrencies' prices even trade-by-trade, we will use little bit more coarse data, since overly fine granularity might suffer for some cryptocurrencies from significant portion of zero ticks (observations, where no trade and/or search took place).

- Objects of interest – initial set of the selected cryptocurrencies was based on Elendner et al. (2016), where ten leading cryptocurrencies were investigated. However, due to either absence of trading pair with Euro or to non-unique name only four remained (more discussed in section 3.3.2). Those four are Bitcoin (XBT), Ethereum (ETH), Litecoin (LTC) and Monero (XMR).

3.2 Cryptocurrency market data

Our first data set come from Kraken Bitcoin exchange, where cryptocurrencies are traded against each other as well as against fiat currencies. Moreover, "Kraken is renowned for being central to liquidity and for its high volume of Bitcoin exchanges in Euro" (Ibinex, 2018). Also, Kraken enables a user friendly API (Application Programming Interface) and possibility to download entire trading history. The guideline for Kraken API is available at *https://www.kraken.com/help/api*. There is a package "Rbitcoin" in R with a function "market.api.query" making interaction with Kraken easier.

3.2.1 Structure

As a cryptocurrency market data we use a trading history of pairs XBT/EUR, ETH/EUR, LTC/EUR and XMR/EUR. Data are available in trade-by-trade granularity, where each realised transaction has following properties: unix time stamp, clearing price in EUR, volume in corresponding cryptocurrency, bid/ask indicator referring whether trade was initiated by buy or sell side and market/limit referring whether the trade was based on market or limit order. We aggregate these data to 1 minute blocks to match them with our SVI data. Further we do not distinguish between bid/ask and market/limit, since we do not examine the market micro-structure, hence the values listed further do not keep this level of detail.

3.2.2 Descriptive statistics

After qualitative data description we shall proceed with their quantitative description. For sample description we utilise following metrics: number of observations, mean, minimum and maximum value, kurtosis, skewness and in the end we test using Jarque–Bera statistics, whether our data are standard normally distributed.

	XBT	ETH	LTC	XMR
n	527,099	527,099	527,099	527,099
mean	< 0.001	< 0.001	< 0.001	< 0.001
minimum	−0.530*	−0.305*	−0.111*	−0.084
maximum	0.560*	0.343*	0.115*	0.077*
kurtosis	29,141.450	3,597.816	68.553	37.426
skewness	9.372	3.875	0.386	0.111
Jarque–Bera *(p value)*	< 0.01	< 0.01	< 0.01	< 0.01

*driven by Kraken outage

Table 3.1: Descriptive statistics for the cryptocurrencies log returns, in granularity of 1 minute

An outstanding values are the minimal and maximal returns. Except only one case, which is minimal return for Monero, all of them happened on 13^{th} January 2018 after Kraken suffered two days long outage. The data suggest, that the highest bid orders accumulated over that period were executed first, thus causing the excessive gain. Then the consequent trading operated within normal values generating this significant drop right after the time of Kraken outage, where all first trades were done at enormous price and then returned back to normal. Another striking value is kurtosis having high value driven by significant share of zero ticks. In order to isolate this effect we might consider data in 15 minutes granularity, where kurtosis is significantly smaller due to reduction of zero ticks. More information about zero ticks is in Section 3.2.3.

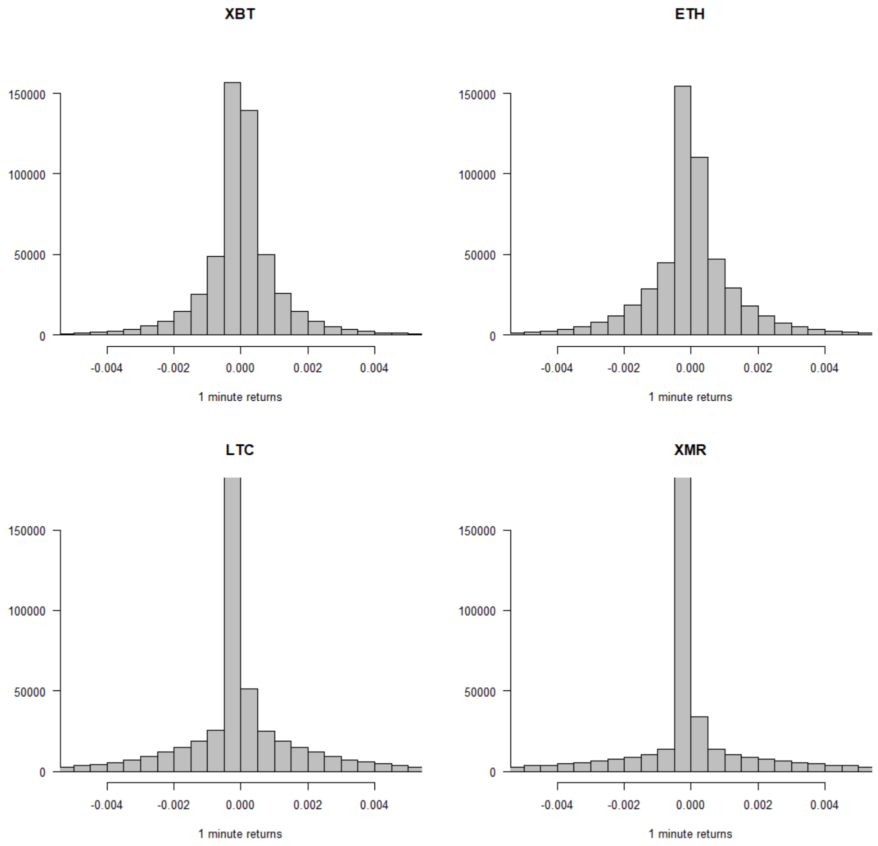

Figure 3.1: Distribution of 1 minute returns of tracked cryptocurrencies

As suggested by summary statistics, we see a disproportionate share of zero or close-to-zero returns. Therefore, we consider moving to more coarse data to get closer to normal distribution and reduce the number of zero ticks.

	XBT	ETH	LTC	XMR
n	$35,140$	$35,140$	$35,140$	$35,140$
mean	< 0.001	< 0.001	< 0.001	< 0.001
min	-0.076	-0.0998	-0.163	-0.104
max	0.098	0.140	0.141	0.175
kurtosis	23.688	27.889	32.458	26.494
skewness	0.401	0.637	0.557	0.789
Jarque–Bera *(p value)*	< 0.01	< 0.01	< 0.01	< 0.01

Table 3.2: Descriptive statistics for the cryptocurrencies log returns, in granularity of 15 minutes

Interestingly enough, in case of 15 minutes data the Kraken outage and consequent disturbance in trading does not contribute neither to minimal or maximal returns. Minimal returns were reached by all the currencies in similar time on 22^{nd} December 2017 after 7am UTC, but maximal returns were reached in different time for each currency. Also skewness is in case of 15 minutes data quite close to zero, but the data remain strongly leptokurtic, but not due to zero ticks as shown in Section 3.2.3.

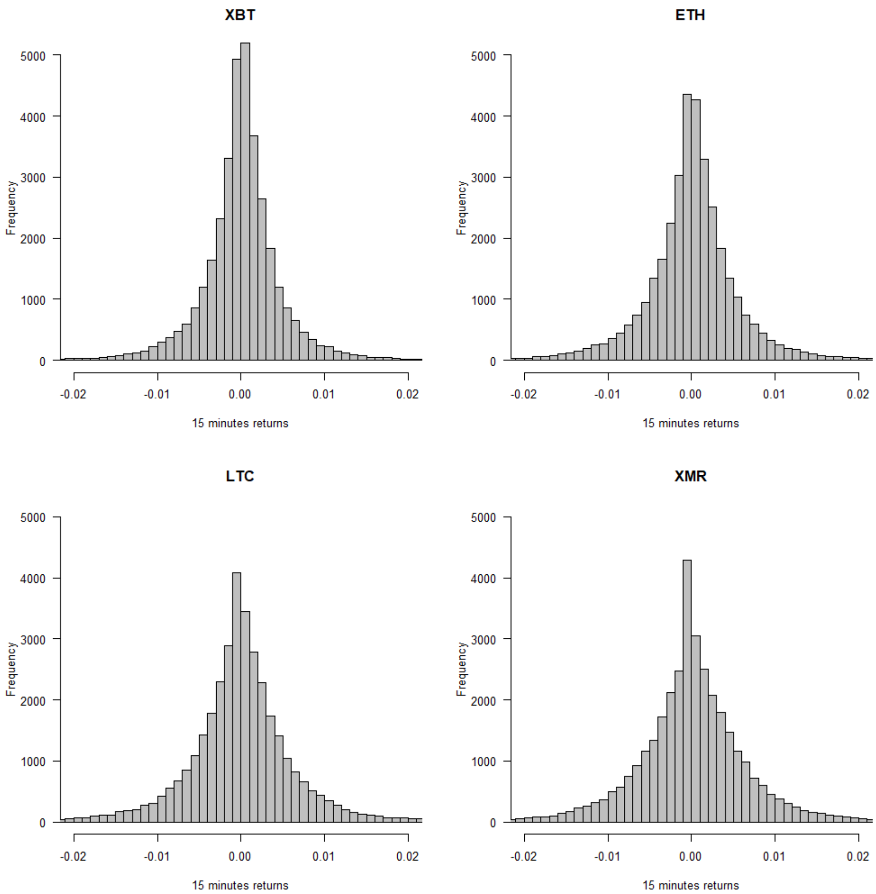

Figure 3.2: Distribution of 15 minute returns of tracked cryptocurrencies

Even by naked eye we can clearly see, that the data are closer to normal distribution and the share of returns close to zero is significantly reduced.

3.2.3 Liquidity

In this section we aim to prove, that market is liquid enough for our analyses. To do so, we check a number of transactions over the entire time period, traded volume expressed as number of currency unit traded and traded value expressed in EUR.

	XBT	ETH	LTC	XMR
transactions in total	13,090,000	8,770,000	2,473,000	1,335,000
traded volume	3,516,342	28,261,386	16,114,408	4,063,686
traded value	$20.9 * 10^9$	$11.1 * 10^9$	$1,5 * 10^9$	$595 * 10^6$
transactions per minute	24.83	16.64	4.69	2.53
traded volume per minute	6.67	53.62	30.57	7.71
traded value per minute	39,669.17	21,042.15	2755.88	1128.96

Table 3.3: Kraken-based market descriptive statistics

As we have seen in case of histograms as well as is visible in Table 3.2.3, Bitcoin should not suffer from zero ticks, since almost 25 transactions per minute on average should be enough. On the contrary, Monero has on average only 2.5 transaction per minute, thus we need to check for the zero tick. Next Figure 3.2.3 illustrates share of zero ticks as function of granularity.

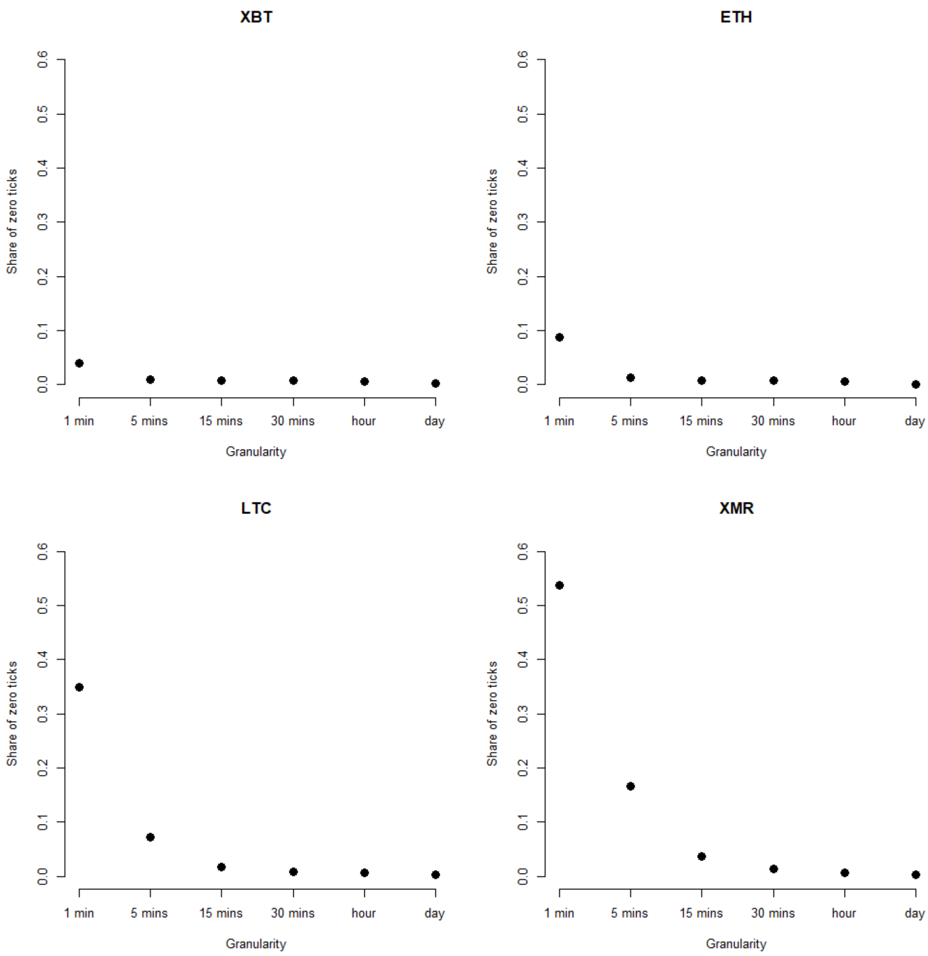

Figure 3.3: Share of observations with no trade as a function of granularity

While Bitcoin or Ethereum does not suffer from too many zero ticks even at minute granularity, Monero has their share over 50%, which decreases bellow 20% in 5 minutes granularity. Therefore, we use 15 minutes granularity as a baseline, because for this granularity all currencies have less than 10% of zero ticks.

3.3 Search volume data

Google Trends enabled us to see, how much have been certain expression “googled”. We call this expression a “keyword” and its search volume serves us as a proxy for an attention allocated to object it describes. This section clarifies how we sampled the data and describes their quality.

3.3.1 Collecting the data

Google offers the user interface on *https://trends.google.com*, which should serve as a main interaction point with Google database. Yet, it possess a set of very stringent restrictions:

- Decreasing granularity – Google offers finest data only for the last few hours. In other words, the further back we look, the more coarse the data are. For instance, if we look one year back, we can get only daily data or looking one week back, we can get only hourly data.
- No mass export – Google enables download of the data in csv format only for displayed period. Ignoring first restriction, it would theoretically mean to download 4-hour blocks for each currency for whole year to get minutely data, theoretically implying $8,760$ manual downloads.
- Scaling – Google does not return absolute number of searches, but rather take maximum of the observed period, mark it as 100 and scale other observations in the period accordingly. Thus, if we want to have index for longer period of time, we need to partially overlap these small periods and scale them. We use 25% overlap and label this process “stitching”. The major drawback is an increase in number of required downloads.

To overcome this limitations, there exists a pseudo API for Google Trends in Python within package “pytrends”. This allows an automated download of multiple 4-hour blocks, but Google protects itself against mass data scraping. There is a limit of queries per day per IP address, which is estimated to be around $2,000$ per day - once our query has been rejected reaching 870 per day and once we managed to get almost $4,000$ per day. Therefore, those estimated $2,000$ is based solely on reported experience of other users and should be considered as purely indicative.

3.3.2 Keywords for SVI

Once we have set up a way for data scraping, we need to find out a proper keywords. A crucial criterion for selecting a keyword is it not having multiple meanings. That disqualifies for example cryptocurrency "Dash", which is a standard word in English and we are not capable to distinguish attention allocated to cryptocurrency and dash as character, but distribution of searches in time and by region helps us to conclude, that cryptocurrency is not the main driver (compare Figures A.1 and A.2 in Appendix). Google offers to filter results by categories and offers even category "finance" (Cat. 7), however the mechanism of this filtering is unknown, thus we do not use the filtering option and rather use only keywords without any sign of ambiguity.

Furthermore, we considered using keywords valid for the cryptocurrency market in general, for instance "blockchain", "cryptocurrency" or "coinbase". Even though inclusion of so called cross-correlated keywords sounds logical, it would bring a series question of how far we should go. Should we include "mining"? Once we include "mining" should we include "gpu"? Since we are interested in short-term effect, we assume that the more general the term is, the longer time it needs to impact the price. For example, looking for GPU might have an impact on Ethereum or Monero price as they are mineable on GPU, but lag between searching for GPU, launching mining rig and therefore influencing supply side would likely exceeds hour or day horizon. Due to aforementioned reasons we employ only keywords based on names of our cryptocurrencies.

Google search engine is case insensitive, but what happens, if users misspell the word? We also control for potential misspells. Running five test for a broad set of keywords we can conclude, that misspellings are insignificant (for complete overview of tested keywords and their relevance please see Table B.1 in Appendix).

After applying filters mentioned above, our final sample consists of four keywords – "bitcoin", "ethereum", "litecoin" and "monero".

3.3.3 Zero search observations

Analogically to liquidity for the cryptocurrency market we also analyse the SVI data, namely zero-search observations. On the contrary to trading, amount of zero-search periods is in case of SVI negligible – under no circumstances exceeding 2% as displayed in Figure 3.4.

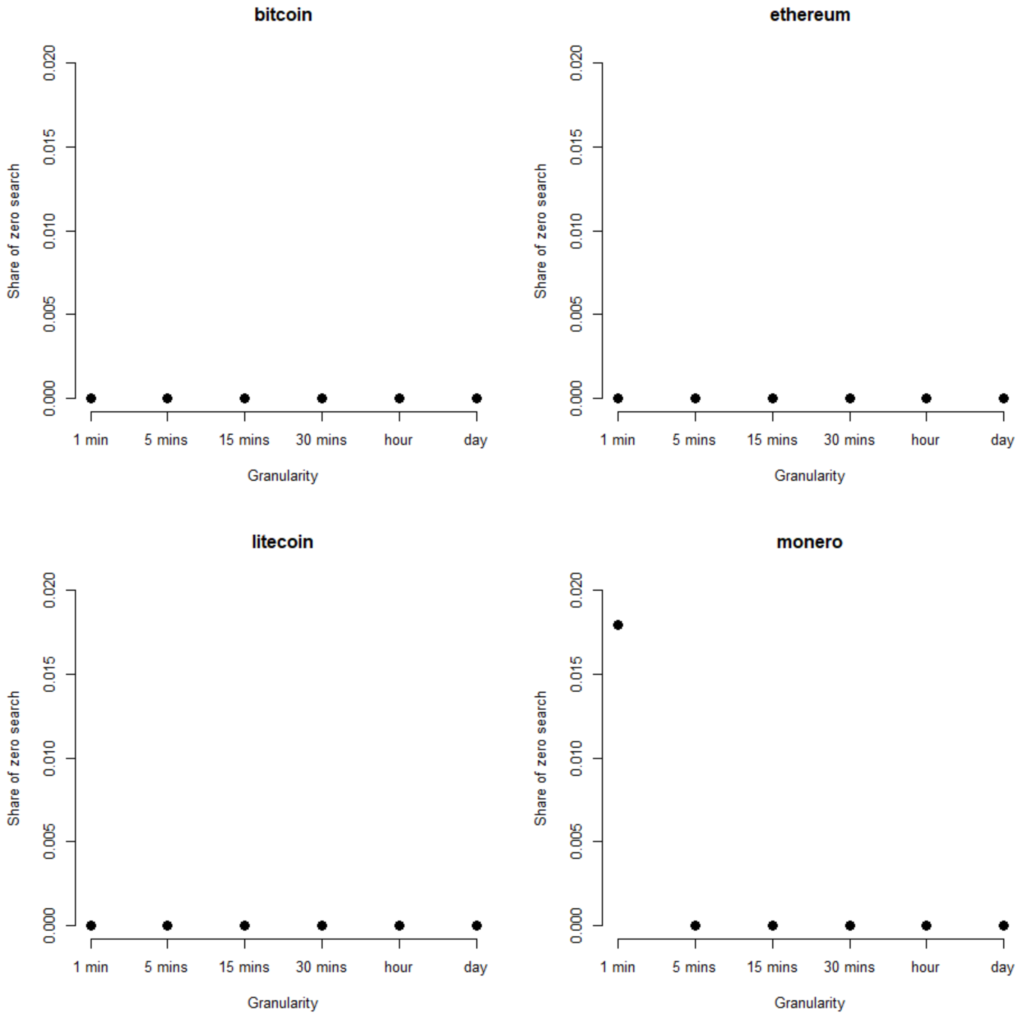

Figure 3.4: Share of observations with no search as a function of granularity

3.4 CRIX

The last data source we use is CRyptocurrency IndeX (CRIX), which is a benchmark for the cryptocurrency market and is based on Trimborn and Härdle (2016). Detailed information about its methodology and its current values can be found at *http://thecrix.de/*. In a nutshell and as stated at its web page, "The CRIX is a market index and follows for the derivation the Laspeyres Index" where market capitalization of traded cryptocurrencies is used. We use development of CRIX as an indicator of overall market mood as described in Section 2.5.

4 Results

This section provides an overview of the results and is divided into three subsections. First, we examine an outcome of statistical tests performed on our sample. Consequently, we present statistical performance of models, namely share of periods with prediction, MDA and MSE. The last subsection compares a trading performance of all employed models. The results provided in this section are either aggregated/averaged or maximal/minimal. Detailed output tables for obtained performance metrics for each of the 256 models and set-ups are shown in Appendix (Table B.2 to B.225)

4.1 Tests results

The first step is to verify whether the series are stationary or whether we need to differentiate them.

KPSS	XBT	ETH	LTC	XMR
price	< 0.01	< 0.01	< 0.01	< 0.01
returns	> 0.1	> 0.1	> 0.1	> 0.1
log returns	> 0.1	> 0.1	> 0.1	> 0.1
SVI	< 0.01	< 0.01	< 0.01	< 0.01
differenced SVI	> 0.1	< 0.01	< 0.01	< 0.01
log differenced SVI	> 0.1	> 0.1	> 0.1	> 0.1

ADF	XBT	ETH	LTC	XMR
price	0.876	0.738	0.749	0.780
returns	< 0.01	< 0.01	< 0.01	< 0.01
log returns	< 0.01	< 0.01	< 0.01	< 0.01
SVI	< 0.01	< 0.01	< 0.01	< 0.01
differenced SVI	< 0.01	< 0.01	< 0.01	< 0.01
log differenced SVI	< 0.01	< 0.01	< 0.01	< 0.01

Table 4.1: Stationarity testing

Based on the test results we proceed further with log-differentiated series for all the series of cryptocurrency prices and its indices of search volume. Theoretically, first level differentiation would be enough for cryptocurrency price, but using log-returns is considered as the best practice (Box and Jenkins, 1976).

Next metric we investigate is the Granger causality. We verify whether the following variables contribute to explaining cryptocurrency return: a Search Volume Index (svi) with no attention differentiation, product of SVI and positive dummy in binary attention differentiation ($svi * D^+_{bin}$), product of SVI and negative dummy in quartile attention differentiation ($svi * D^-_{quart}$) or product of SVI and positive dummy in quartile attention differentiation ($svi * D^+_{quart}$). We consider Granger causality with lags $1, 3, 5, 10$ and 15 for each of the cryptocurrency in 15 minutes granularity as per Figure 4.1.

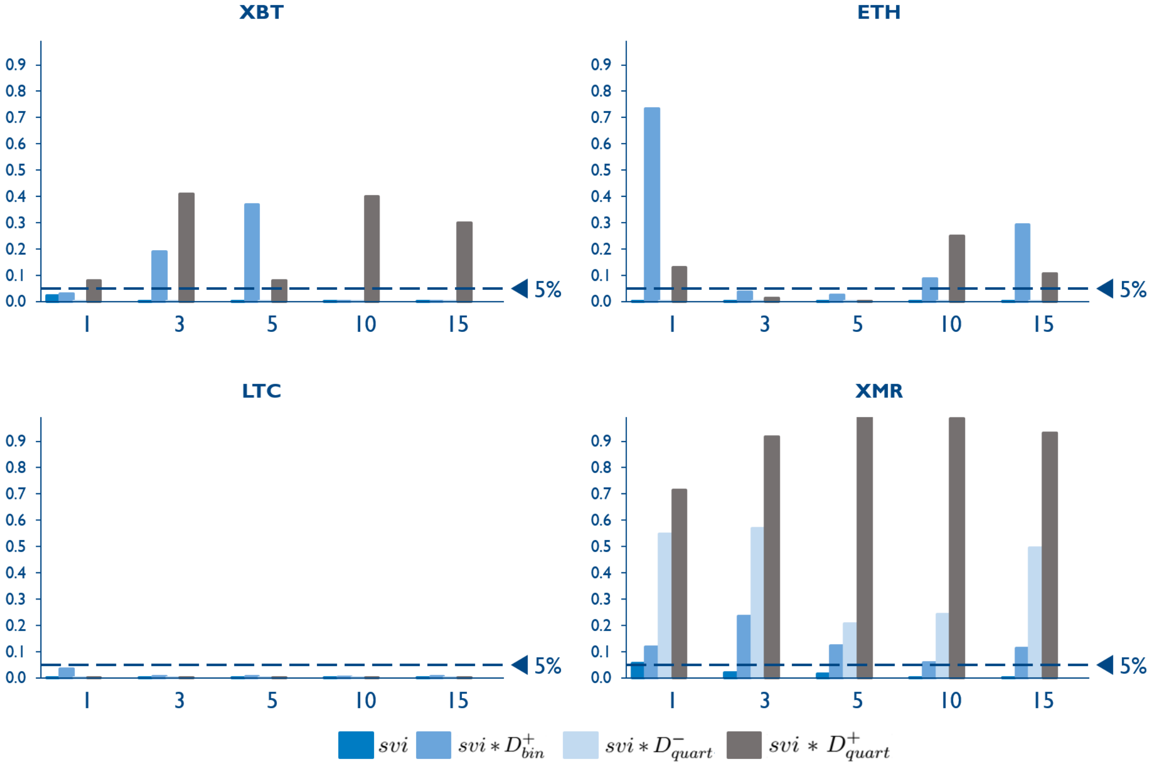

Figure 4.1: Granger causality p-values for different lags and different cryptocurrencies, 15 minutes granularity

Overall, from the Figure 4.1 we might conclude, that pure svi has always an explanatory power regardless the lags order and cryptocurrency. After considering the dummy variables, we observe p-value for H_0 (explanatory variable not being relevant) of SVI with differentiated attention being not always below 0.05 threshold, however it is below it at least in some cases. This supports our naked eye observations discussed in Introduction, Section 1.

The last statistics we test is cointegration. It tells us whether we should proceed with VAR model or VECM and if so, how many cointegration vectors are there.

	Cointegration vectors	Trace test	p-value	Likelihood test	p-value
$r_{XBT} + svi_{XBT}$	0	130.89	< 0.01	133.91	< 0.01
$r_{XBT} + svi_{XBT}$	1	3.02	> 0.1	3.02	> 0.1
$r_{ETH} + svi_{ETH}$	0	95.15	< 0.01	98.32	< 0.01
$r_{ETH} + svi_{ETH}$	1	3.17	> 0.1	3.17	> 0.1
$r_{LTC} + svi_{LTC}$	0	223.03	< 0.01	227.75	< 0.01
$r_{LTC} + svi_{LTC}$	1	4.72	> 0.1	4.72	> 0.1
$r_{XMR} + svi_{XMR}$	0	231.93	< 0.01	236.23	< 0.01
$r_{XMR} + svi_{XMR}$	1	4.3	> 0.1	4.3	> 0.1

Table 4.2: Results of Johansen test for cointegration

The results of Johansen test for all cryptocurrencies suggest using VECM due to a presence of one cointegration vector. Therefore, all further multivariate analyses results are based on VECM.

4.2 Model performance

First we compare the share of periods, where a model is able to give a prediction for next period. Generally, there are two reasons why the models fail to predict. The univariate models (ARMA and ARIMA) are treated slightly different: the models are almost always able to give a prediction, thus we define a non-functional period as a period when sum of p and q (orders of AR and MA part) is equal to zero. That means, we would be using prediction based solely on constant, which is in vast majority of cases equal to zero and therefore yielding forecast of zero movement for next period and that is highly unlikely. Nevertheless, no prediction or predicting zero movement yields the same command for trading model - Hold. Multivariate models (VAR and VECM) fail to predict in case we cannot find inverse matrix ("system is exactly singular"), which is in majority of situations caused by including dummy variable that has only one value in corresponding window. In our case, during the learning period we observed only positive attention, therefore the model would not be capable of identifying an effect of positive attention, because there was no observation of "base case". Further, we call model (2.1) "univariate". We refer to forms of multivariate model "SVI" and form of SVI inclusion. It means we have "SVI not differenced" corresponding to model (2.2), "SVI binary" corresponding to model (2.4) and "SVI quartiles" corresponding to model (2.6). This holds for VAR models as well as for their VECM counterparts.

	Univariate	SVI not differenced	SVI binary	SVI quartiles
15 minutes (average)	**0.664**	**0.991**	**0.630**	**0.440**
1/2 day	0.383	0.996	0.317	0.024
1 day	0.541	0.996	0.528	0.242
3 days	0.826	0.992	0.797	0.666
1 week	0.908	0.981	0.877	0.830
30 minutes (average)	**0.721**	**0.983**	**0.755**	**0.602**
1 day	0.389	0.995	0.461	0.056
3 days	0.705	0.992	0.775	0.638
1 week	0.878	0.981	0.868	0.821
2 weeks	0.913	0.962	0.917	0.893
1 hour (average)	**0.637**	**0.982**	**0.806**	**0.612**
2 days	0.364	0.995	0.646	0.076
4 days	0.548	0.989	0.800	0.681
1 week	0.750	0.981	0.862	0.807
2 weeks	0.885	0.962	0.916	0.887
1 hour (average)	**0.337**	**0.919**	**0.599**	**0.123**
2 weeks	0.265	0.962	0.428	0.067
3 weeks	0.313	0.943	0.577	0.106
4 weeks	0.364	0.884	0.670	0.170
6 weeks	0.406	0.885	0.723	0.148

Table 4.3: Share of periods with functional model, averaged over cryptocurrencies

From the Table 4.3 we can see, that SVI without differencing is the most versatile model. What might be unexpected is, that SVI with binary differentiation is quite often more versatile than univariate implying the market mood is changing frequently enough. As expected, SVI with quartile differentiation has the lowest share of prediction made, especially when comparing the shortest and longer learning period irrespective the granularity. After examining the average values we focus on the best performing situation for each model, granularity and learning period.

	Univariate	SVI not differenced	SVI binary	SVI quartiles
15 minutes (average)	**0.735**	**0.992**	**0.632**	**0.441**
1/2 day	0.426	0.997	0.320	0.024
1 day	0.628	0.997	0.531	0.244
3 days	0.910	0.992	0.797	0.666
1 week	0.975	0.981	0.878	0.830
30 minutes (average)	**0.801**	**0.983**	**0.756**	**0.602**
1 day	0.449	0.997	0.463	0.057
3 days	0.834	0.992	0.776	0.638
1 week	0.960	0.981	0.868	0.821
2 weeks	0.962	0.962	0.917	0.893
1 hour (average)	**0.741**	**0.982**	**0.807**	**0.614**
2 days	0.457	0.995	0.649	0.077
4 days	0.682	0.989	0.800	0.682
1 week	0.873	0.981	0.864	0.808
2 weeks	0.952	0.962	0.916	0.888
1 hour (average)	**0.410**	**0.920**	**0.611**	**0.135**
2 weeks	0.320	0.962	0.432	0.071
3 weeks	0.385	0.943	0.587	0.109
4 weeks	0.454	0.888	0.678	0.180
6 weeks	0.481	0.885	0.746	0.178

Table 4.4: Share of periods with functional model, maximal values

As suggested before, the maximal values do not differ much from average ones in case of SVI with attention differentiation. It is caused by the fact, that attention identification mechanism is same for all the cryptocurrencies. It differs significantly in case of univariate, where there are apparently cryptocurrencies, whose returns are more often autocorrelated than the others. Still, SVI with quartile differentiation is the least versatile, while the SVI with binary differentiation is outperforming univariate for more coarse granularities and it holds for both maximal values as well for average ones.

The next step after comparing when models predict is to compare how they predict. For that purpose we utilise MDA and MSE metrics. Due directional prediction being the input for the command in our trading simulation, the MDA is the crucial one, thus we start with MDA values averaged over cryptocurrencies for each granularity and learning period. Subsequently, we continue with maximal one, analogically to previous approach.

	Univariate	SVI not differenced	SVI binary	SVI quartiles
15 minutes (average)	**0.534**	**0.519**	**0.512**	**0.499**
1/2 day	0.537	0.521	0.510	0.493
1 day	0.537	0.518	0.519	0.504
3 days	0.531	0.521	0.504	0.500
1 week	0.532	0.518	0.514	0.500
30 minutes (average)	**0.536**	**0.518**	**0.514**	**0.511**
1 day	0.532	0.518	0.505	0.523
3 days	0.540	0.517	0.518	0.509
1 week	0.539	0.519	0.520	0.510
2 weeks	0.535	0.518	0.513	0.502
1 hour (average)	**0.531**	**0.516**	**0.512**	**0.501**
2 days	0.533	0.517	0.516	0.505
4 days	0.526	0.513	0.502	0.489
1 week	0.536	0.519	0.520	0.506
2 weeks	0.528	0.516	0.512	0.504
1 hour (average)	**0.547**	**0.513**	**0.517**	**0.487**
2 weeks	0.534	0.534	0.547	0.574
3 weeks	0.550	0.517	0.525	0.471
4 weeks	0.551	0.493	0.510	0.451
6 weeks	0.556	0.509	0.486	0.452

Table 4.5: 1-step ahead MDA, averaged over cryptocurrencies

A positive outcome is, that majority of the models delivers MDA over 0.5 meaning they have a value added compared to random guessing. This benchmark assumes movements up and down being close to 50:50 ratio. In our case, it is not a very strong assumption as this ratio takes value for different cryptocurrencies and granularities relatively close to it. On average, the univariate is the best performing model in terms of MDA, constantly being by 1 to 2 percentage points better than models using Google search volume.

	Univariate	SVI not differenced	SVI binary	SVI quartiles
15 minutes (average)	**0.552**	**0.538**	**0.529**	**0.511**
1/2 day	0.551	0.539	0.528	0.503
1 day	0.556	0.537	0.539	0.514
3 days	0.547	0.536	0.514	0.518
1 week	0.552	0.538	0.534	0.509
30 minutes (average)	**0.545**	**0.525**	**0.520**	**0.522**
1 day	0.538	0.525	0.511	0.546
3 days	0.550	0.523	0.524	0.514
1 week	0.548	0.529	0.526	0.521
2 weeks	0.543	0.524	0.519	0.506
1 hour (average)	**0.541**	**0.525**	**0.520**	**0.514**
2 days	0.542	0.529	0.524	0.518
4 days	0.538	0.520	0.511	0.508
1 week	0.545	0.525	0.525	0.522
2 weeks	0.539	0.527	0.518	0.509
1 hour (average)	**0.576**	**0.538**	**0.557**	**0.561**
2 weeks	0.554	0.560	0.571	0.727
3 weeks	0.563	0.533	0.577	0.513
4 weeks	0.597	0.512	0.523	0.525
6 weeks	0.590	0.546	0.555	0.477

Table 4.6: Maximal 1-step ahead MDA for each granularity and learning period

On the other hand, comparing models' best performance we see that univariate can be in certain cases outperformed by models utilizing Google search volume. Compared to univariate they are more dependent on the selection of learning period and the cryptocurrency itself. In other words, the benefit of including Google search volume is different for each of the cryptocurrency, which is in line with different values of the Granger causality for each of the cryptocurrency.

	Univariate	SVI not differenced	SVI binary	SVI quartiles
15 minutes (average)	**0.015**	**0.019**	**0.023**	**0.413**
1/2 day	0.017	0.020	0.020	0.333
1 day	0.013	0.017	0.018	0.054
3 days	0.018	0.022	0.035	1.166
1 week	0.014	0.018	0.018	0.097
30 minutes (average)	**0.030**	**0.038**	**0.046**	**1.079**
1 day	0.039	0.041	0.069	3.576
3 days	0.027	0.036	0.039	0.195
1 week	0.026	0.035	0.037	0.123
2 weeks	0.030	0.038	0.041	0.425
1 hour (average)	**0.064**	**0.071**	**0.089**	**3.156**
2 days	0.055	0.069	0.076	1.127
4 days	0.085	0.077	0.128	9.008
1 week	0.053	0.066	0.071	0.695
2 weeks	0.065	0.072	0.080	1.794
1 hour (average)	**2.530**	**19.813**	**10.422**	**910.849**
2 weeks	3.475	3.431	4.755	1,840.393
3 weeks	2.390	5.717	7.550	454.973
4 weeks	2.163	67.617	11.666	869.109
6 weeks	2.093	2.488	17.717	478.924

Table 4.7: 1-step ahead MSE, averaged over cryptocurrencies

Looking at MSE we might conclude, that on average inclusion of Google search volume does not improve precision of the prediction. Interestingly, MSE for SVI using quartile differentiation is also relatively high. That is probably driven by lack of observations for states of dummy variables, since this is more evident for short learning periods making the impact of dummy variable responsible for attention differentiation exaggerated. It is counter-intuitive, but having best MDA and worst MSE is not necessarily contradiction. For instance, predicting 50% growth, when only 5% growth has been observed, would yield higher MSE than −1% prediction, but better MDA. Also the trading performance would be better for 50% prediction than −1%.

	Univariate	SVI not differenced	SVI binary	SVI quartiles
15 minutes (average)	**0.009**	**0.011**	**0.012**	**0.263**
1/2 day	0.010	0.012	0.018	0.791
1 day	0.009	0.011	0.011	0.182
3 days	0.008	0.011	0.010	0.050
1 week	0.007	0.010	0.010	0.030
30 minutes (average)	**0.017**	**0.022**	**0.027**	**0.720**
1 day	0.020	0.023	0.039	2.419
3 days	0.017	0.022	0.023	0.281
1 week	0.015	0.021	0.022	0.115
2 weeks	0.015	0.022	0.022	0.065
1 hour (average)	**0.033**	**0.044**	**0.051**	**2.271**
2 days	0.040	0.046	0.071	6.708
4 days	0.032	0.043	0.045	1.183
1 week	0.030	0.043	0.044	0.695
2 weeks	0.030	0.042	0.045	0.498
1 hour (average)	**1.245**	**14.838**	**6.822**	**604.494**
2 weeks	1.636	2.171	4.267	1,435.962
3 weeks	1.116	4.467	5.217	206.962
4 weeks	1.178	51.104	7.018	396.517
6 weeks	1.049	1.609	10.786	378.535

Table 4.8: Minimal 1-step ahead MSE for each granularity and learning period

Focusing on the best performing models in terms of MSE, we can conclude generally the same as for averaged values. However, it is necessary to keep in mind, that for example SVI with no differentiation makes prediction in more than 99% of periods, which means, it predicts even in periods, when autocorrelation patterns are not present. That might make the SVI with no differentiation appear as performing worse, but to conclude that, it would be necessary to compare it on same periods. We benchmark it on the entire sample, since that is necessary to make trading simulation comparable, which is the ultimate measure for the models. The next subsection covers it in more detail.

4.3 Trading simulation

After examining statistical qualities of the models we should investigate how they perform in the quasi-real world. There are two major drivers for aforementioned motivation. First of all, MSE is of limited usefulness in our trading scheme, where we only want to know, whether the market will go up or down. Also, even identical MDAs value might not be equal, meaning, that having MDA of 0.6 while predicting successfully small market movements and missing big changes, might be worse than having MDA of 0.58 but catching all the major changes. In other words, statistics consider all MDA values equal, but their trading impact might differ. In order to mitigate that, we have performed trading simulation with following set-ups and results. First set-up is assuming ideal world with no transaction costs and thus 0.00% fee per transaction.

	Univariate	SVI not differenced	SVI binary	SVI quartiles
15 minutes (average)	**67,984.20**	**11,990.86**	**1,761.48**	**22.51**
1/2 day	47.36	339.49	5.64	1.09
1 day	1,110.30	9,682.51	53.77	2.27
3 days	23,956.58	20,311.42	1,888.81	13.31
1 week	246,822.54	17,630.00	5,097.71	73.36
30 minutes (average)	**2,647.25**	**407.31**	**315.70**	**19.26**
1 day	14.76	225.22	3.96	3.21
3 days	344.49	297.39	89.97	6.63
1 week	4,585.96	462.31	421.12	40.64
2 weeks	5,643.78	644.33	747.75	26.54
1 hour (average)	**48.46**	**37.95**	**45.13**	**3.33**
2 days	7.20	21.59	5.25	1.96
4 days	13.68	40.24	24.13	3.96
1 week	60.46	40.59	58.71	4.25
2 weeks	112.48	49.38	92.43	3.15
1 hour (average)	**1.97**	**2.04**	**2.33**	**2.87**
2 weeks	2.10	2.88	2.59	4.27
3 weeks	2.16	1.81	3.55	3.10
4 weeks	1.69	1.34	1.70	2.89
6 weeks	1.93	2.13	1.51	1.24

Table 4.9: Annual return of simulated trading with 0% fee for each granularity and learning period, averaged over cryptocurrencies

Under such circumstances, the best performing models on average are the models with the finest granularity and the highest number of trades. Both of these conditions are met by univariate and SVI with no differentiation in granularity of 15 minutes, especially with longer learning periods. However, it is necessary to mention, that annual returns in magnitude of hundred thousands percentage is not achievable and is only driven by the fact, that 15 minutes granularity enables to trade approximately 35,000 times per year, which implies that profit 0.0355% per trade would be enough to get such number, since:

$$1.000355^{35,000} = 250,000$$

Implying the required efficiency of trading is relatively low even for reaching such high returns.

	Univariate	SVI not differenced	SVI binary	SVI quartiles
15 minutes (average)	**247,223.60**	**43,680.81**	**5,933.45**	**37.01**
1/2 day	103.47	717.31	7.42	1.35
1 day	2,989.64	38,018.12	103.56	3.89
3 days	62,707.43	72,786.17	6,516.29	24.90
1 week	923,093.85	63,201.63	17,106.53	117.90
30 minutes (average)	**7,588.69**	**945.42**	**600.22**	**39.59**
1 day	28.21	766.85	5.68	5.08
3 days	644.84	484.09	167.92	9.72
1 week	13,028.15	977.87	683.31	104.11
2 weeks	16,653.56	1,552.88	1,543.98	39.47
1 hour (average)	**65.68**	**56.28**	**93.34**	**5.32**
2 days	12.21	38.95	10.58	3.26
4 days	17.71	57.24	39.41	6.04
1 week	93.03	56.43	126.89	6.25
2 weeks	139.78	72.50	196.50	5.74
1 hour (average)	**2.74**	**3.54**	**4.71**	**5.17**
2 weeks	3.01	6.35	4.45	6.58
3 weeks	2.56	2.21	8.40	5.80
4 weeks	2.13	1.96	2.85	6.46
6 weeks	3.28	3.65	3.12	1.84

Table 4.10: Maximal annual return of simulated trading with 0% fee for each granularity and learning period

The list of the best performing models follows the same pattern. Highest returns are reached by models with as much trading as possible, again by univariate and SVI with no differentiation. It is interesting to mention, that just by halving the granularity, performance goes rapidly down and for example SVI with binary differentiation is performing better than univariate with coarser granularity. To get closer to reality we include 0.1% fee per transaction, that is the lowest taker fee at Kraken. Such set-up delivers the following results:

	Univariate	SVI not differenced	SVI binary	SVI quartiles
15 minutes (average)	**0.14**	**0.13**	**0.08**	**0.61**
1/2 day	0.28	0.14	0.04	0.88
1 day	0.24	0.13	0.04	0.56
3 days	0.01	0.11	0.10	0.38
1 week	0.03	0.15	0.15	0.60
30 minutes (average)	**0.89**	**0.81**	**1.01**	**2.90**
1 day	0.98	0.77	0.11	2.46
3 days	0.68	0.37	0.52	1.53
1 week	1.02	0.72	1.45	5.18
2 weeks	0.89	1.40	1.97	2.43
1 hour (average)	**1.95**	**1.67**	**2.66**	**1.84**
2 days	2.13	1.48	0.44	1.62
4 days	1.60	1.41	1.66	2.02
1 week	2.26	1.54	3.38	2.17
2 weeks	1.80	2.27	5.17	1.53
1 hour (average)	**1.93**	**1.77**	**2.13**	**2.83**
2 weeks	2.07	2.50	2.43	4.23
3 weeks	2.12	1.56	3.25	3.06
4 weeks	1.65	1.14	1.51	2.83
6 weeks	1.88	1.89	1.33	1.21

Table 4.11: Annual return of simulated trading with 0.1% fee for each granularity and learning period, averaged over cryptocurrencies

In contrast to 0% fee we can see, that frequently trading models are below water (ending value smaller than starting value). There are two ways how adding Google search volume is benefiting the trading. In case of univariate vs. SVI with no differentiation we already know, that SVI with no differentiation is functional at biggest share of periods. Thus, it has more options for giving sell/buy command (when model does not predict, it is automatically hold command, see Figure 2.1) leading to higher number of trades. Despite that, it returns comparable performance as univariate with lower number of trades, meaning SVI with no differentiation has "better" distributed correct directional predictions than univariate model. This is an example of MDA not being the fully satisfactory measure, as we have univariate mode with higher MDA but worse trading performance. Another way is the case of SVI with no differentiation vs. SVI with some form of differentiation. Differentiation reduces the number of trades and cherry picks the strongest signals and thus delivers "best" distribution of correct directional predictions, often accompanied by the highest MDA.

	Univariate	SVI not differenced	SVI binary	SVI quartiles
15 minutes (average)	**0.27**	**0.38**	**0.25**	**0.96**
1/2 day	0.57	0.30	0.05	1.09
1 day	0.41	0.25	0.08	1.01
3 days	0.02	0.39	0.34	0.66
1 week	0.08	0.57	0.53	1.07
30 minutes (average)	**1.66**	**1.57**	**1.94**	**5.57**
1 day	1.74	0.98	0.16	3.88
3 days	1.38	0.57	1.01	2.32
1 week	1.72	1.52	2.40	12.81
2 weeks	1.80	3.22	4.18	3.29
1 hour (average)	**2.83**	**3.03**	**5.69**	**2.90**
2 days	2.57	3.90	0.84	2.68
4 days	2.73	2.31	2.73	3.12
1 week	3.49	2.21	7.42	2.99
2 weeks	2.54	3.71	11.77	2.82
1 hour (average)	**2.69**	**3.10**	**4.29**	**5.10**
2 weeks	2.97	5.56	4.14	6.54
3 weeks	2.51	1.91	7.70	5.74
4 weeks	2.09	1.67	2.55	6.33
6 weeks	3.19	3.26	2.75	1.80

Table 4.12: Maximal annual return of simulated trading with 0.1% fee for each granularity and learning period

The same logic applies for the list of the best performing models with 0.1% fee, the dominance of right down corner is getting more visible. To simulate the most harsh conditions on Kraken, i.e. being taker with low trading volume, we impose 0.26% fee per transaction. In such set-up our models deliver following performance:

	Univariate	SVI not differenced	SVI binary	SVI quartiles
15 minutes (average)	**0.00**	**0.00**	**0.00**	**0.17**
1/2 day	0.00	0.00	0.00	0.62
1 day	0.00	0.00	0.00	0.06
3 days	0.00	0.00	0.00	0.00
1 week	0.00	0.00	0.00	0.00
30 minutes (average)	**0.00**	**0.00**	**0.00**	**0.50**
1 day	0.02	0.00	0.00	1.60
3 days	0.00	0.00	0.00	0.15
1 week	0.00	0.00	0.00	0.19
2 weeks	0.00	0.00	0.00	0.05
1 hour (average)	**0.11**	**0.02**	**0.03**	**0.78**
2 days	0.35	0.05	0.01	1.20
4 days	0.07	0.01	0.02	0.69
1 week	0.01	0.01	0.03	0.75
2 weeks	0.00	0.02	0.05	0.48
1 hour (average)	**1.87**	**1.41**	**1.84**	**2.78**
2 weeks	2.02	2.00	2.21	4.18
3 weeks	2.06	1.23	2.81	3.00
4 weeks	1.59	0.88	1.26	2.75
6 weeks	1.81	1.55	1.08	1.18

Table 4.13: Annual return of simulated trading with 0.26% fee for each granularity and learning period, averaged over cryptocurrencies

The sparsity of the trading is now the key, when we see clear dominance of trading with day frequency. Generally, all models trading more frequently spend all the money on the fees ending up with literally no money in the end. The only exception is SVI with quartile differentiation, which is driven by relatively low share of periods, when this model actually gives prediction reducing trading frequency.

	Univariate	SVI not differenced	SVI binary	SVI quartiles
15 minutes (average)	**0.00**	**0.00**	**0.00**	**0.22**
1/2 day	0.00	0.00	0.00	0.78
1 day	0.00	0.00	0.00	0.12
3 days	0.00	0.00	0.00	0.00
1 week	0.00	0.00	0.00	0.00
30 minutes (average)	**0.01**	**0.00**	**0.00**	**0.81**
1 day	0.05	0.00	0.00	2.51
3 days	0.00	0.00	0.00	0.23
1 week	0.00	0.00	0.00	0.45
2 weeks	0.00	0.00	0.00	0.06
1 hour (average)	**0.17**	**0.06**	**0.06**	**1.25**
2 days	0.50	0.17	0.01	1.96
4 days	0.14	0.01	0.04	1.08
1 week	0.03	0.01	0.08	1.08
2 weeks	0.01	0.03	0.13	0.90
1 hour (average)	**2.61**	**2.51**	**3.69**	**5.00**
2 weeks	2.91	4.50	3.69	6.48
3 weeks	2.44	1.52	6.68	5.65
4 weeks	2.03	1.29	2.14	6.13
6 weeks	3.06	2.71	2.26	1.75

Table 4.14: Maximal annual return of simulated trading with 0.26% fee for each granularity and learning period

For third in the row, the list of the best performing models shares the pattern with averaged list. However, there is more visible dominance of models incorporating Google search volume implying, that for cryptocurrency on average it does not contribute that much, but for some cryptocurrencies and some granularities it is more helpful than for the others.

5 Conclusion

Forecasting and nowcasting using Google search volume data has become a trending topic during the last years, especially since Google enabled downloading such data and internet penetration and usage rose substantially. Thus, significant attention has been given to developing models utilizing such data as knowing, what people are searching for, can often serve as a proxy of their future decisions and actions. Together with the fact, that cryptocurrency market has higher share of retail investors than standard stock market (Reuters, 2018), it creates a necessity to investigate whether Google search data could help to anticipate development of cryptocurrency market.

The first part of the thesis examined whether inclusion of Google search volume, represented by Search Volume Index (SVI), could improve a quality of short-term forecasting and trading based on this forecasting. In order to address this, we analysed the role of Google search volumes in the cryptocurrency market forecasting. For this purpose, we compared the performance of pure autoregressive model against three models incorporating Google search volume in several ways which were different in assigning sentiment to the search volume. After performing aforementioned analyses and interpreting results, we can conclude that Google data can help, however, this is only applicable under certain circumstances. The heatmaps below summarize the results.

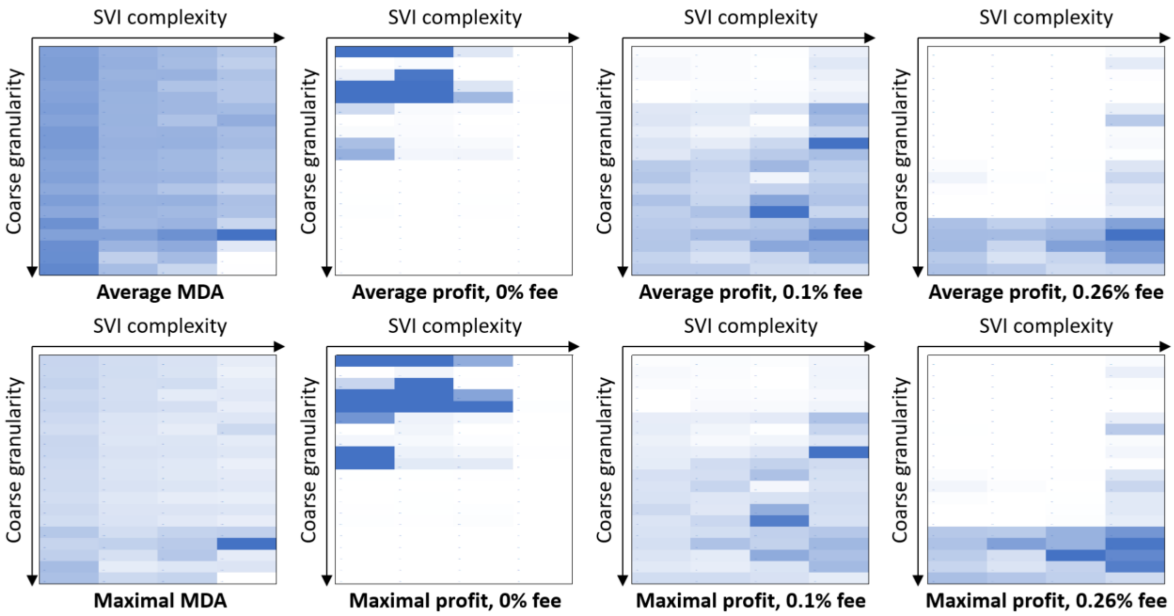

Figure 5.1: Heatmaps of prediction and trading performance

We can see that including Google search volume is not an universal remedy. Nevertheless, it can improve trading performance when compared to univariate model in some cases. These cases is in general lower frequency trading regardless the fees which in is our case day trading and partially hourly trading. Under the assumption of no fees and frequent trading, we observe the univariate model outperforming models with Google search volumes. However, the assumption of no fees is rather strict. When transaction costs are taken into account, frequent trading is no longer viable. Nevertheless, daily and hourly trading, especially when Google search data are included, could still be profitable. Furthermore, considering that underlying assets rose circa between 60% and 150% over the sample period, we get only a handful combinations of learning period, granularity, model and cryptocurrency, when our trading is capable of beating the simple strategy of buying at the beginning, holding and selling at the end of the period. We conclude that using Google search volume for the very fine granularity does not bring significant value added whereas including them for more coarse data leads to model improvements, at least for some of the examined cryptocurrencies.

It is worth mentioning that apart from employing fine granularity data, our work also contributed to developing a way of automated Google Trends data scrapping. This is in contrast with past researchers who used mostly daily data as they faced limitations of Google Trends interface.

A key limitation of our thesis is the lack of capability to distinguish the driver of attention. We can clearly see a change in attention allocated to certain cryptocurrency, but we struggle to distinguish whether it was driven by positive or negative news. Bridging this gap would clearly improve usefulness of Google search volume data since we would be capable to predict major investors' mood changes prior to their interaction with market. Additionally, a more extensive research on search terms connected to our keywords searches and on opened links from the search results page, would help to estimate the investors' mood. Unfortunately, due to limitation from Google side, these data are not at all or barely available at best.

Our thesis suggests two main fields for future research. The first is to focus on how the usefulness of Google search volume changes with the share of retail versus institutional investors. The idea behind it lays on the assumption that institutional investors use Google search less often and hence they likely produce less traffic with respect to the value of invested funds. Another field to investigate is how changes benefits from incorporating Google search volume under different market regimes. In other words, whether Google search volume value added is different under bullish and bearish markets and whether it differs with respect to volatility both in the short-term as well as in the long-term.

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A Figures

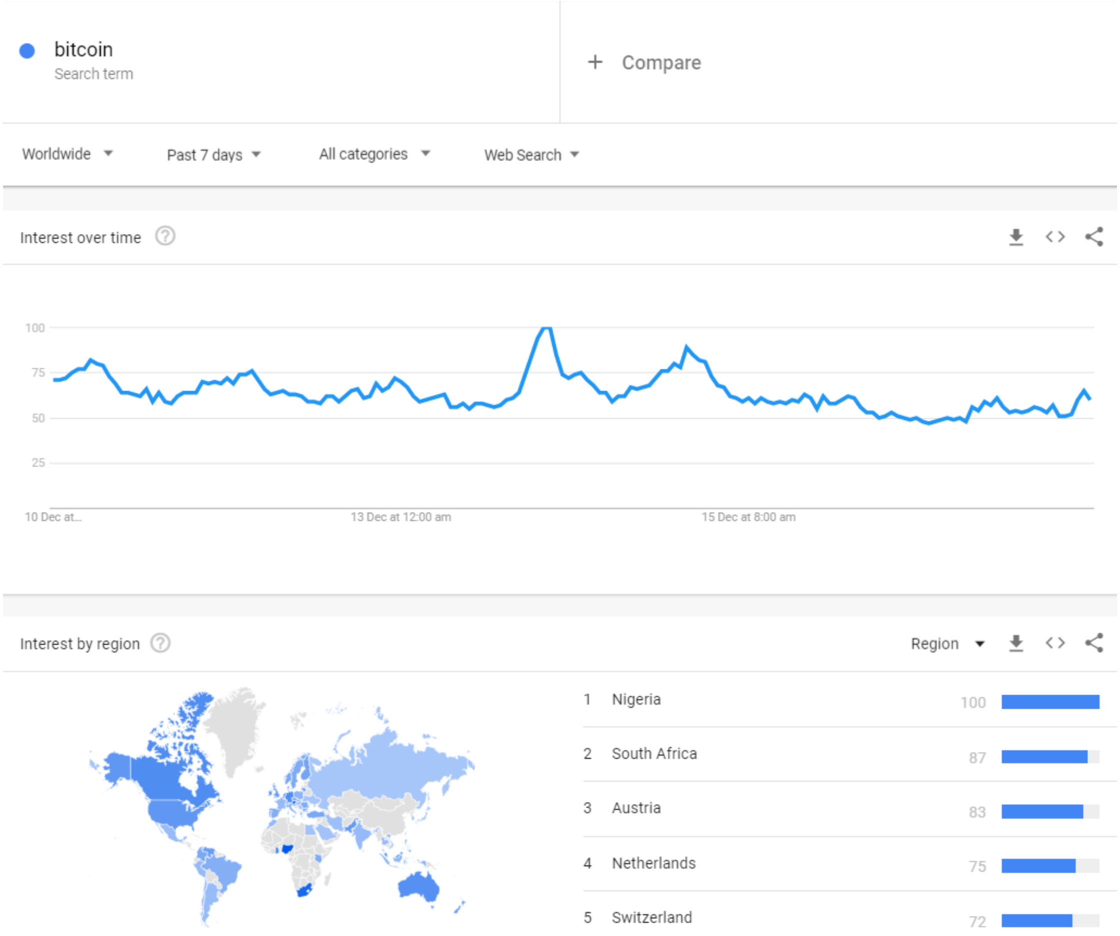

Figure A.1: Example of unique keyword's search volume patterns

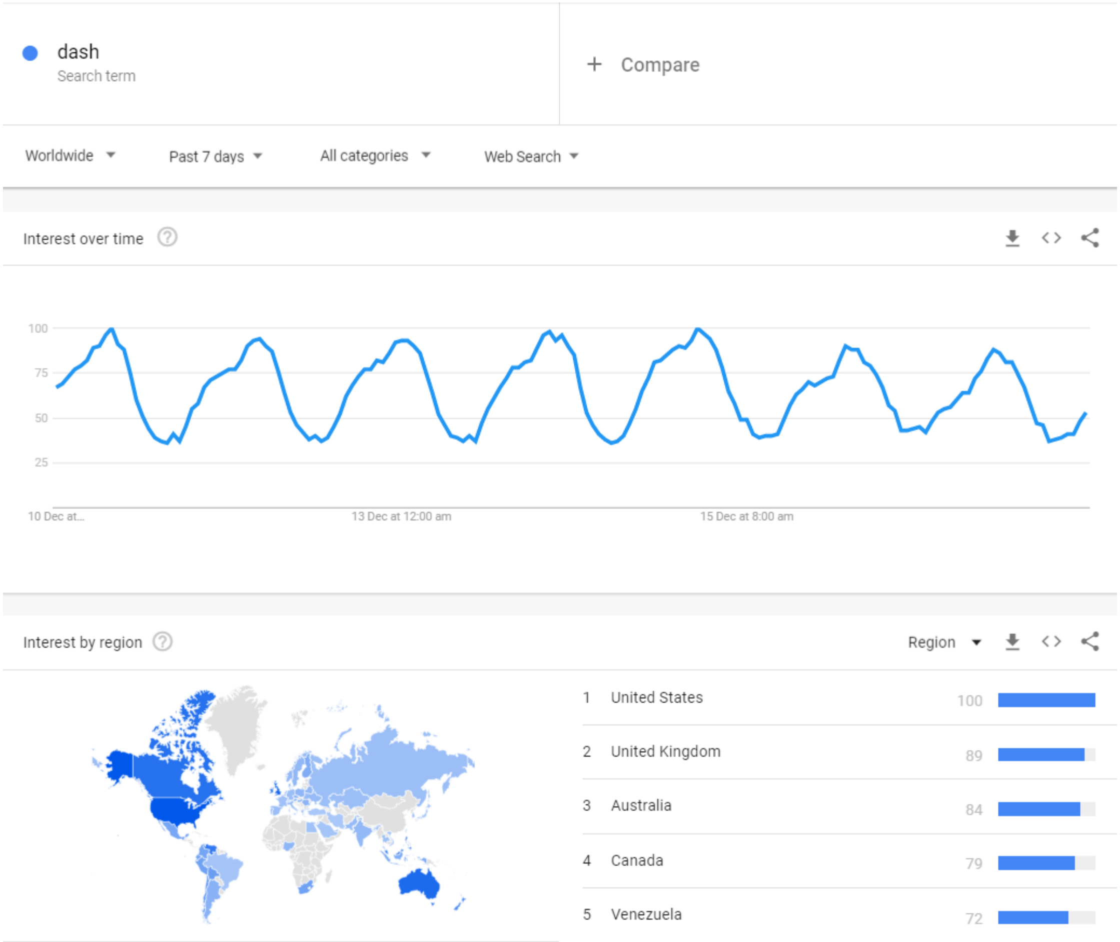

Figure A.2: Example of in English ambiguous keyword's search volume patterns

B Tables

Keyword	Misspell	% of zero ticks	Misspell	% of zero ticks
Bitcoin	bytcoin	> 99%	bitecoin	> 99%
Bitcoin	bytecoin	> 85%	bitcion	> 99%
Ethereum	etherem	> 99%	etereum	> 99%
Ethereum	eterem	> 99%	aether	> 95%
Litecoin	litcoin	> 95%	lytecoin	> 99%
Litecoin	lytcoin	> 99%	litcion	> 99%
Monero	monoro	> 99%	menero	> 99%
Monero	moneto	> 99%	menoro	> 99%

Table B.1: Considered misspellings and their relevance

XBT 15 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1/2 day	0.547	0.528	0.514	0.501
1 day	0.550	0.530	0.516	0.495
3 days	0.552	0.528	0.526	0.509
1 week	0.555	0.529	0.531	0.513

Table B.2: Complete MDA results for XBT with 15 minutes granularity, segmented by model and learning period, 1-step ahead prediction

XBT 15 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1/2 day	0.512	0.507	0.492	0.510
1 day	0.523	0.508	0.499	0.495
3 days	0.523	0.506	0.504	0.500
1 week	0.524	0.506	0.507	0.505

Table B.3: Complete MDA results for XBT with 15 minutes granularity, segmented by model and learning period, 3-steps ahead prediction

XBT 15 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1/2 day	0.503	0.500	0.490	0.488
1 day	0.516	0.502	0.501	0.489
3 days	0.517	0.498	0.498	0.499
1 week	0.516	0.500	0.497	0.502

Table B.4: Complete MDA results for XBT with 15 minutes granularity, segmented by model and learning period, 5-steps ahead prediction

XBT 15 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1/2 day	0.491	0.491	0.491	0.472
1 day	0.506	0.494	0.495	0.486
3 days	0.509	0.490	0.490	0.498
1 week	0.508	0.492	0.491	0.501

Table B.5: Complete MDA results for XBT with 15 minutes granularity, segmented by model and learning period, 10-steps ahead prediction

XBT 15 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1/2 day	0.497	0.493	0.489	0.428
1 day	0.503	0.498	0.484	0.496
3 days	0.506	0.490	0.492	0.506
1 week	0.510	0.493	0.498	0.507

Table B.6: Complete MDA results for XBT with 15 minutes granularity, segmented by model and learning period, 15-steps ahead prediction

ETH 15 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1/2 day	0.546	0.536	0.514	0.518
1 day	0.551	0.539	0.528	0.503
3 days	0.548	0.538	0.534	0.506
1 week	0.556	0.537	0.539	0.514

Table B.7: Complete MDA results for ETH with 15 minutes granularity, segmented by model and learning period, 1-step ahead prediction

ETH 15 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1/2 day	0.518	0.518	0.495	0.525
1 day	0.524	0.517	0.507	0.498
3 days	0.524	0.513	0.511	0.503
1 week	0.528	0.514	0.510	0.502

Table B.8: Complete MDA results for ETH with 15 minutes granularity, segmented by model and learning period, 3-steps ahead prediction

ETH 15 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1/2 day	0.503	0.507	0.493	0.518
1 day	0.514	0.505	0.497	0.501
3 days	0.511	0.502	0.498	0.501
1 week	0.519	0.504	0.499	0.499

Table B.9: Complete MDA results for ETH with 15 minutes granularity, segmented by model and learning period, 5-steps ahead prediction

ETH 15 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1/2 day	0.484	0.493	0.483	0.476
1 day	0.509	0.499	0.491	0.494
3 days	0.506	0.492	0.486	0.493
1 week	0.512	0.494	0.484	0.492

Table B.10: Complete MDA results for ETH with 15 minutes granularity, segmented by model and learning period, 10-steps ahead prediction

ETH 15 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1/2 day	0.489	0.495	0.490	0.444
1 day	0.506	0.500	0.494	0.494
3 days	0.502	0.493	0.490	0.493
1 week	0.510	0.493	0.474	0.492

Table B.11: Complete MDA results for ETH with 15 minutes granularity, segmented by model and learning period, 15-steps ahead prediction

LTC 15 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1/2 day	0.522	0.514	0.499	0.503
1 day	0.529	0.512	0.503	0.496
3 days	0.527	0.508	0.502	0.500
1 week	0.528	0.507	0.505	0.498

Table B.12: Complete MDA results for LTC with 15 minutes granularity, segmented by model and learning period, 1-step ahead prediction

LTC 15 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1/2 day	0.502	0.498	0.497	0.486
1 day	0.513	0.504	0.494	0.492
3 days	0.511	0.497	0.494	0.501
1 week	0.512	0.494	0.495	0.495

Table B.13: Complete MDA results for LTC with 15 minutes granularity, segmented by model and learning period, 3-steps ahead prediction

LTC 15 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1/2 day	0.487	0.489	0.499	0.518
1 day	0.503	0.491	0.484	0.491
3 days	0.503	0.486	0.485	0.497
1 week	0.507	0.481	0.483	0.493

Table B.14: Complete MDA results for LTC with 15 minutes granularity, segmented by model and learning period, 5-steps ahead prediction

LTC 15 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1/2 day	0.474	0.483	0.496	0.507
1 day	0.489	0.486	0.487	0.502
3 days	0.499	0.480	0.480	0.502
1 week	0.503	0.476	0.481	0.494

Table B.15: Complete MDA results for LTC with 15 minutes granularity, segmented by model and learning period, 10-steps ahead prediction

LTC 15 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1/2 day	0.470	0.483	0.479	0.471
1 day	0.484	0.484	0.494	0.494
3 days	0.496	0.479	0.487	0.497
1 week	0.498	0.478	0.486	0.499

Table B.16: Complete MDA results for LTC with 15 minutes granularity, segmented by model and learning period, 15-steps ahead prediction

XMR 15 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1/2 day	0.507	0.504	0.489	0.478
1 day	0.516	0.502	0.491	0.478
3 days	0.502	0.498	0.494	0.485
1 week	0.507	0.498	0.499	0.491

Table B.17: Complete MDA results for XMR with 15 minutes granularity, segmented by model and learning period, 1-step ahead prediction

XMR 15 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1/2 day	0.507	0.503	0.487	0.485
1 day	0.519	0.499	0.491	0.485
3 days	0.511	0.495	0.495	0.490
1 week	0.511	0.496	0.495	0.494

Table B.18: Complete MDA results for XMR with 15 minutes granularity, segmented by model and learning period, 3-steps ahead prediction

XMR 15 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1/2 day	0.500	0.497	0.486	0.513
1 day	0.516	0.494	0.489	0.490
3 days	0.506	0.491	0.492	0.492
1 week	0.506	0.489	0.494	0.494

Table B.19: Complete MDA results for XMR with 15 minutes granularity, segmented by model and learning period, 5-steps ahead prediction

XMR 15 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1/2 day	0.485	0.490	0.493	0.510
1 day	0.501	0.489	0.488	0.497
3 days	0.502	0.483	0.490	0.495
1 week	0.497	0.480	0.484	0.496

Table B.20: Complete MDA results for XMR with 15 minutes granularity, segmented by model and learning period, 10-steps ahead prediction

XMR 15 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1/2 day	0.489	0.492	0.496	0.465
1 day	0.492	0.492	0.495	0.486
3 days	0.497	0.486	0.499	0.488
1 week	0.496	0.483	0.485	0.499

Table B.21: Complete MDA results for XMR with 15 minutes granularity, segmented by model and learning period, 15-steps ahead prediction

XBT 30 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1 day	0.538	0.525	0.511	0.505
3 days	0.542	0.524	0.516	0.504
1 week	0.547	0.523	0.522	0.509
2 weeks	0.548	0.522	0.523	0.521

Table B.22: Complete MSE results for XBT with 30 minutes granularity, segmented by model and learning period, 1-step ahead prediction

XBT 30 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1 day	0.508	0.504	0.486	0.505
3 days	0.518	0.503	0.493	0.502
1 week	0.522	0.494	0.496	0.508
2 weeks	0.525	0.495	0.492	0.518

Table B.23: Complete MDA results for XBT with 30 minutes granularity, segmented by model and learning period, 3-steps ahead prediction

XBT 30 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1 day	0.500	0.496	0.486	0.501
3 days	0.510	0.495	0.485	0.499
1 week	0.518	0.490	0.484	0.504
2 weeks	0.516	0.489	0.479	0.513

Table B.24: Complete MDA results for XBT with 30 minutes granularity, segmented by model and learning period, 5-steps ahead prediction

XBT 30 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1 day	0.502	0.508	0.474	0.512
3 days	0.511	0.497	0.493	0.498
1 week	0.512	0.492	0.486	0.509
2 weeks	0.513	0.499	0.486	0.517

Table B.25: Complete MDA results for XBT with 30 minutes granularity, segmented by model and learning period, 10-steps ahead prediction

XBT 30 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1 day	0.499	0.502	0.489	0.494
3 days	0.511	0.493	0.484	0.492
1 week	0.514	0.491	0.477	0.514
2 weeks	0.516	0.494	0.480	0.524

Table B.26: Complete MDA results for XBT with 30 minutes granularity, segmented by model and learning period, 15-steps ahead prediction

ETH 30 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1 day	0.535	0.522	0.502	0.545
3 days	0.543	0.521	0.519	0.506
1 week	0.550	0.522	0.524	0.506
2 weeks	0.548	0.529	0.526	0.509

Table B.27: Complete MDA results for ETH with 30 minutes granularity, segmented by model and learning period, 1-step ahead prediction

ETH 30 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1 day	0.518	0.505	0.492	0.542
3 days	0.514	0.505	0.497	0.499
1 week	0.522	0.504	0.501	0.497
2 weeks	0.516	0.505	0.504	0.505

Table B.28: Complete MDA results for ETH with 30 minutes granularity, segmented by model and learning period, 3-steps ahead prediction

ETH 30 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1 day	0.514	0.505	0.494	0.544
3 days	0.509	0.499	0.491	0.499
1 week	0.520	0.497	0.491	0.501
2 weeks	0.514	0.495	0.487	0.509

Table B.29: Complete MDA results for ETH with 30 minutes granularity, segmented by model and learning period, 5-steps ahead prediction

ETH 30 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1 day	0.503	0.506	0.493	0.574
3 days	0.504	0.499	0.497	0.503
1 week	0.517	0.503	0.491	0.505
2 weeks	0.510	0.500	0.477	0.511

Table B.30: Complete MDA results for ETH with 30 minutes granularity, segmented by model and learning period, 10-steps ahead prediction

ETH 30 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1 day	0.508	0.503	0.505	0.549
3 days	0.504	0.500	0.503	0.493
1 week	0.511	0.500	0.498	0.497
2 weeks	0.505	0.496	0.481	0.504

Table B.31: Complete MDA results for ETH with 30 minutes granularity, segmented by model and learning period, 15-steps ahead prediction

LTC 30 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1 day	0.529	0.511	0.504	0.546
3 days	0.532	0.511	0.506	0.499
1 week	0.537	0.513	0.516	0.505
2 weeks	0.531	0.510	0.515	0.502

Table B.32: Complete MDA results for LTC with 30 minutes granularity, segmented by model and learning period, 1-step ahead prediction

LTC 30 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1 day	0.497	0.495	0.491	0.507
3 days	0.510	0.494	0.488	0.497
1 week	0.507	0.491	0.492	0.497
2 weeks	0.513	0.487	0.490	0.500

Table B.33: Complete MDA results for LTC with 30 minutes granularity, segmented by model and learning period, 3-steps ahead prediction

LTC 30 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1 day	0.483	0.494	0.493	0.508
3 days	0.500	0.485	0.481	0.495
1 week	0.503	0.482	0.484	0.499
2 weeks	0.512	0.483	0.482	0.499

Table B.34: Complete MDA results for LTC with 30 minutes granularity, segmented by model and learning period, 5-steps ahead prediction

LTC 30 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1 day	0.468	0.485	0.498	0.521
3 days	0.489	0.480	0.487	0.500
1 week	0.496	0.476	0.494	0.510
2 weeks	0.503	0.482	0.486	0.502

Table B.35: Complete MDA results for LTC with 30 minutes granularity, segmented by model and learning period, 10-steps ahead prediction

LTC 30 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1 day	0.488	0.492	0.504	0.503
3 days	0.498	0.487	0.489	0.502
1 week	0.501	0.484	0.507	0.520
2 weeks	0.505	0.486	0.487	0.515

Table B.36: Complete MDA results for LTC with 30 minutes granularity, segmented by model and learning period, 15-steps ahead prediction

XMR 30 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1 day	0.525	0.514	0.502	0.494
3 days	0.522	0.514	0.510	0.500
1 week	0.524	0.511	0.511	0.514
2 weeks	0.530	0.515	0.514	0.509

Table B.37: Complete MDA results for XMR with 30 minutes granularity, segmented by model and learning period, 1-step ahead prediction

XMR 30 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1 day	0.511	0.496	0.488	0.491
3 days	0.501	0.495	0.493	0.504
1 week	0.503	0.496	0.492	0.511
2 weeks	0.508	0.501	0.497	0.509

Table B.38: Complete MDA results for XMR with 30 minutes granularity, segmented by model and learning period, 3-steps ahead prediction

XMR 30 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1 day	0.499	0.491	0.482	0.489
3 days	0.494	0.489	0.482	0.500
1 week	0.496	0.490	0.480	0.508
2 weeks	0.507	0.493	0.484	0.509

Table B.39: Complete MDA results for XMR with 30 minutes granularity, segmented by model and learning period, 5-steps ahead prediction

XMR 30 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1 day	0.489	0.496	0.490	0.508
3 days	0.487	0.492	0.490	0.504
1 week	0.499	0.488	0.479	0.517
2 weeks	0.506	0.491	0.486	0.515

Table B.40: Complete MDA results for XMR with 30 minutes granularity, segmented by model and learning period, 10-steps ahead prediction

XMR 30 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1 day	0.482	0.494	0.486	0.521
3 days	0.479	0.491	0.482	0.507
1 week	0.497	0.490	0.479	0.513
2 weeks	0.499	0.490	0.488	0.518

Table B.41: Complete MDA results for XMR with 30 minutes granularity, segmented by model and learning period, 15-steps ahead prediction

XBT 1 hour	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 days	0.533	0.520	0.503	0.483
4 days	0.532	0.527	0.516	0.506
1 week	0.542	0.529	0.522	0.518
2 weeks	0.545	0.525	0.521	0.522

Table B.42: Complete MSE results for XBT with 1 hour granularity, segmented by model and learning period, 1-step ahead prediction

XBT 1 hour	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 days	0.508	0.497	0.476	0.496
4 days	0.503	0.497	0.491	0.502
1 week	0.511	0.495	0.487	0.507
2 weeks	0.517	0.496	0.481	0.518

Table B.43: Complete MDA results for XBT with 1 hour granularity, segmented by model and learning period, 3-steps ahead prediction

XBT 1 hour	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 days	0.520	0.502	0.479	0.519
4 days	0.511	0.495	0.483	0.499
1 week	0.516	0.499	0.489	0.506
2 weeks	0.523	0.496	0.483	0.509

Table B.44: Complete MDA results for XBT with 1 hour granularity, segmented by model and learning period, 5-steps ahead prediction

XBT 1 hour	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 days	0.517	0.496	0.473	0.499
4 days	0.510	0.492	0.472	0.483
1 week	0.511	0.500	0.474	0.503
2 weeks	0.518	0.494	0.464	0.515

Table B.45: Complete MDA results for XBT with 1 hour granularity, segmented by model and learning period, 10-steps ahead prediction

XBT 1 hour	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 days	0.523	0.495	0.475	0.492
4 days	0.505	0.483	0.473	0.474
1 week	0.507	0.493	0.476	0.488
2 weeks	0.518	0.496	0.469	0.503

Table B.46: Complete MDA results for XBT with 1 hour granularity, segmented by model and learning period, 15-steps ahead prediction

ETH 1 hour	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 days	0.538	0.513	0.511	0.488
4 days	0.539	0.519	0.518	0.508
1 week	0.540	0.517	0.524	0.511
2 weeks	0.541	0.523	0.525	0.506

Table B.47: Complete MDA results for ETH with 1 hour granularity, segmented by model and learning period, 1-step ahead prediction

ETH 1 hour	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 days	0.513	0.492	0.484	0.522
4 days	0.503	0.498	0.483	0.507
1 week	0.515	0.499	0.496	0.505
2 weeks	0.508	0.491	0.497	0.505

Table B.48: Complete MDA results for ETH with 1 hour granularity, segmented by model and learning period, 3-steps ahead prediction

ETH 1 hour	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 days	0.514	0.494	0.490	0.532
4 days	0.506	0.505	0.489	0.515
1 week	0.518	0.500	0.487	0.504
2 weeks	0.510	0.497	0.492	0.499

Table B.49: Complete MDA results for ETH with 1 hour granularity, segmented by model and learning period, 5-steps ahead prediction

ETH 1 hour	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 days	0.503	0.497	0.493	0.548
4 days	0.504	0.511	0.488	0.507
1 week	0.521	0.504	0.481	0.510
2 weeks	0.515	0.498	0.487	0.493

Table B.50: Complete MDA results for ETH with 1 hour granularity, segmented by model and learning period, 10-steps ahead prediction

ETH 1 hour	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 days	0.508	0.494	0.496	0.514
4 days	0.513	0.507	0.484	0.522
1 week	0.517	0.508	0.486	0.518
2 weeks	0.516	0.505	0.488	0.487

Table B.51: Complete MDA results for ETH with 1 hour granularity, segmented by model and learning period, 15-steps ahead prediction

LTC 1 hour	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 days	0.516	0.502	0.492	0.478
4 days	0.529	0.506	0.504	0.494
1 week	0.524	0.511	0.503	0.493
2 weeks	0.528	0.507	0.512	0.502

Table B.52: Complete MDA results for LTC with 1 hour granularity, segmented by model and learning period, 1-step ahead prediction

LTC 1 hour	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 days	0.486	0.480	0.484	0.487
4 days	0.497	0.490	0.489	0.490
1 week	0.502	0.494	0.484	0.486
2 weeks	0.505	0.498	0.484	0.503

Table B.53: Complete MDA results for LTC with 1 hour granularity, segmented by model and learning period, 3-steps ahead prediction

LTC 1 hour	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 days	0.482	0.481	0.493	0.520
4 days	0.496	0.483	0.500	0.487
1 week	0.501	0.486	0.496	0.487
2 weeks	0.502	0.495	0.494	0.502

Table B.54: Complete MDA results for LTC with 1 hour granularity, segmented by model and learning period, 5-steps ahead prediction

LTC 1 hour	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 days	0.493	0.488	0.514	0.529
4 days	0.505	0.500	0.512	0.483
1 week	0.507	0.494	0.517	0.488
2 weeks	0.501	0.495	0.511	0.507

Table B.55: Complete MDA results for LTC with 1 hour granularity, segmented by model and learning period, 10-steps ahead prediction

LTC 1 hour	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 days	0.495	0.490	0.523	0.521
4 days	0.497	0.499	0.522	0.481
1 week	0.499	0.489	0.531	0.508
2 weeks	0.497	0.499	0.510	0.518

Table B.56: Complete MDA results for LTC with 1 hour granularity, segmented by model and learning period, 15-steps ahead prediction

XMR 1 hour	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 days	0.518	0.518	0.502	0.508
4 days	0.511	0.512	0.511	0.509
1 week	0.527	0.512	0.513	0.498
2 weeks	0.530	0.520	0.520	0.494

Table B.57: Complete MDA results for XMR with 1 hour granularity, segmented by model and learning period, 1-step ahead prediction

XMR 1 hour	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 days	0.511	0.501	0.481	0.489
4 days	0.498	0.500	0.499	0.501
1 week	0.509	0.500	0.495	0.503
2 weeks	0.501	0.504	0.498	0.493

Table B.58: Complete MDA results for XMR with 1 hour granularity, segmented by model and learning period, 3-steps ahead prediction

XMR 1 hour	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 days	0.514	0.496	0.485	0.478
4 days	0.492	0.495	0.493	0.495
1 week	0.512	0.497	0.491	0.502
2 weeks	0.514	0.499	0.492	0.491

Table B.59: Complete MDA results for XMR with 1 hour granularity, segmented by model and learning period, 5-steps ahead prediction

XMR 1 hour	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 days	0.488	0.491	0.475	0.478
4 days	0.488	0.493	0.484	0.498
1 week	0.500	0.500	0.486	0.508
2 weeks	0.507	0.499	0.490	0.495

Table B.60: Complete MDA results for XMR with 1 hour granularity, segmented by model and learning period, 10-steps ahead prediction

XMR 1 hour	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 days	0.493	0.487	0.484	0.471
4 days	0.500	0.484	0.485	0.498
1 week	0.496	0.486	0.488	0.503
2 weeks	0.495	0.484	0.501	0.485

Table B.61: Complete MDA results for XMR with 1 hour granularity, segmented by model and learning period, 15-steps ahead prediction

XBT 1 day	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 weeks	0.547	0.560	0.551	0.615
3 weeks	0.560	0.516	0.577	0.475
4 weeks	0.530	0.480	0.514	0.424
6 weeks	0.580	0.546	0.498	0.447

Table B.62: Complete MSE results for XBT with 1 day granularity, segmented by model and learning period, 1-step ahead prediction

XBT 1 day	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 weeks	0.530	0.536	0.581	0.731
3 weeks	0.574	0.515	0.519	0.500
4 weeks	0.530	0.488	0.500	0.470
6 weeks	0.526	0.560	0.533	0.553

Table B.63: Complete MDA results for XBT with 1 day granularity, segmented by model and learning period, 3-steps ahead prediction

XBT 1 day	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 weeks	0.564	0.566	0.578	0.577
3 weeks	0.610	0.525	0.540	0.325
4 weeks	0.536	0.498	0.502	0.394
6 weeks	0.540	0.547	0.579	0.532

Table B.64: Complete MDA results for XBT with 1 day granularity, segmented by model and learning period, 5-steps ahead prediction

XBT 1 day	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 weeks	0.581	0.562	0.543	0.654
3 weeks	0.603	0.553	0.538	0.475
4 weeks	0.555	0.509	0.496	0.439
6 weeks	0.509	0.542	0.504	0.447

Table B.65: Complete MDA results for XBT with 1 day granularity, segmented by model and learning period, 10-steps ahead prediction

XBT 1 day	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 weeks	0.649	0.545	0.538	0.500
3 weeks	0.594	0.554	0.490	0.375
4 weeks	0.560	0.535	0.491	0.515
6 weeks	0.491	0.562	0.464	0.426

Table B.66: Complete MDA results for XBT with 1 day granularity, segmented by model and learning period, 15-steps ahead prediction

ETH 1 day	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 weeks	0.554	0.523	0.571	0.538
3 weeks	0.533	0.501	0.498	0.421
4 weeks	0.597	0.512	0.523	0.439
6 weeks	0.544	0.503	0.415	0.477

Table B.67: Complete MDA results for ETH with 1 day granularity, segmented by model and learning period, 1-step ahead prediction

ETH 1 day	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 weeks	0.594	0.530	0.542	0.654
3 weeks	0.607	0.497	0.562	0.500
4 weeks	0.629	0.449	0.492	0.439
6 weeks	0.571	0.486	0.428	0.523

Table B.68: Complete MDA results for ETH with 1 day granularity, segmented by model and learning period, 3-steps ahead prediction

ETH 1 day	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 weeks	0.594	0.534	0.500	0.615
3 weeks	0.598	0.487	0.551	0.579
4 weeks	0.621	0.512	0.506	0.439
6 weeks	0.565	0.484	0.414	0.538

Table B.69: Complete MDA results for ETH with 1 day granularity, segmented by model and learning period, 5-steps ahead prediction

ETH 1 day	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 weeks	0.505	0.562	0.530	0.500
3 weeks	0.561	0.471	0.539	0.526
4 weeks	0.540	0.508	0.492	0.485
6 weeks	0.510	0.524	0.431	0.508

Table B.70: Complete MDA results for ETH with 1 day granularity, segmented by model and learning period, 10-steps ahead prediction

ETH 1 day	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 weeks	0.571	0.537	0.510	0.385
3 weeks	0.598	0.509	0.485	0.474
4 weeks	0.533	0.527	0.530	0.545
6 weeks	0.486	0.540	0.453	0.523

Table B.71: Complete MDA results for ETH with 1 day granularity, segmented by model and learning period, 15-steps ahead prediction

LTC 1 day	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 weeks	0.538	0.537	0.506	0.727
3 weeks	0.543	0.533	0.488	0.513
4 weeks	0.542	0.481	0.492	0.414
6 weeks	0.508	0.478	0.477	0.463

Table B.72: Complete MDA results for LTC with 1 day granularity, segmented by model and learning period, 1-step ahead prediction

LTC 1 day	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 weeks	0.462	0.510	0.592	0.682
3 weeks	0.522	0.494	0.557	0.538
4 weeks	0.533	0.467	0.514	0.500
6 weeks	0.542	0.483	0.490	0.444

Table B.73: Complete MDA results for LTC with 1 day granularity, segmented by model and learning period, 3-steps ahead prediction

LTC 1 day	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 weeks	0.551	0.486	0.564	0.636
3 weeks	0.500	0.516	0.531	0.564
4 weeks	0.523	0.481	0.480	0.483
6 weeks	0.554	0.500	0.477	0.463

Table B.74: Complete MDA results for LTC with 1 day granularity, segmented by model and learning period, 5-steps ahead prediction

LTC 1 day	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 weeks	0.584	0.510	0.556	0.500
3 weeks	0.500	0.524	0.481	0.513
4 weeks	0.514	0.508	0.506	0.517
6 weeks	0.488	0.511	0.512	0.593

Table B.75: Complete MDA results for LTC with 1 day granularity, segmented by model and learning period, 10-steps ahead prediction

LTC 1 day	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 weeks	0.600	0.528	0.517	0.409
3 weeks	0.449	0.569	0.510	0.436
4 weeks	0.520	0.531	0.494	0.362
6 weeks	0.413	0.521	0.555	0.519

Table B.76: Complete MDA results for LTC with 1 day granularity, segmented by model and learning period, 15-steps ahead prediction

XMR 1 day	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 weeks	0.495	0.514	0.561	0.417
3 weeks	0.563	0.516	0.538	0.474
4 weeks	0.533	0.498	0.512	0.525
6 weeks	0.590	0.509	0.555	0.420

Table B.77: Complete MDA results for XMR with 1 day granularity, segmented by model and learning period, 1-step ahead prediction

XMR 1 day	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 weeks	0.484	0.499	0.538	0.583
3 weeks	0.563	0.535	0.531	0.447
4 weeks	0.548	0.534	0.539	0.390
6 weeks	0.580	0.464	0.490	0.480

Table B.78: Complete MDA results for XMR with 1 day granularity, segmented by model and learning period, 3-steps ahead prediction

XMR 1 day	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 weeks	0.484	0.517	0.606	0.667
3 weeks	0.571	0.510	0.515	0.526
4 weeks	0.556	0.517	0.566	0.525
6 weeks	0.606	0.469	0.500	0.420

Table B.79: Complete MDA results for XMR with 1 day granularity, segmented by model and learning period, 5-steps ahead prediction

XMR 1 day	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 weeks	0.516	0.510	0.539	0.375
3 weeks	0.580	0.559	0.552	0.395
4 weeks	0.609	0.520	0.603	0.525
6 weeks	0.604	0.542	0.478	0.500

Table B.80: Complete MDA results for XMR with 1 day granularity, segmented by model and learning period, 10-steps ahead prediction

XMR 1 day	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 weeks	0.611	0.522	0.452	0.458
3 weeks	0.603	0.563	0.462	0.474
4 weeks	0.583	0.511	0.541	0.508
6 weeks	0.602	0.585	0.506	0.420

Table B.81: Complete MDA results for XMR with 1 day granularity, segmented by model and learning period, 15-steps ahead prediction

XBT 15 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1/2 day	0.010	0.012	0.018	0.791
1 day	0.009	0.011	0.011	0.182
3 days	0.008	0.011	0.010	0.050
1 week	0.007	0.010	0.010	0.030

Table B.82: Complete MSE results for XBT with 15 minutes granularity, segmented by model and learning period, 1-step ahead prediction

XBT 15 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1/2 day	0.027	0.062	0.156	19.193
1 day	0.023	0.058	0.078	3.937
3 days	0.019	0.055	0.060	0.926
1 week	0.018	0.052	0.055	0.396

Table B.83: Complete MSE results for XBT with 15 minutes granularity, segmented by model and learning period, 3-steps ahead prediction

XBT 15 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1/2 day	0.047	0.152	0.797	132.351
1 day	0.037	0.143	0.309	23.472
3 days	0.030	0.132	0.179	5.261
1 week	0.028	0.125	0.150	1.824

Table B.84: Complete MSE results for XBT with 15 minutes granularity, segmented by model and learning period, 5-steps ahead prediction

XBT 15 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1/2 day	0.112	0.594	16.942	1,456.849
1 day	0.082	0.529	4.772	364.128
3 days	0.064	0.479	1.311	79.924
1 week	0.059	0.439	0.904	24.238

Table B.85: Complete MSE results for XBT with 15 minutes granularity, segmented by model and learning period, 10-steps ahead prediction

XBT 15 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1/2 day	0.246	1.450	136.096	5,438.145
1 day	0.170	1.231	38.718	1,429.888
3 days	0.134	1.079	7.178	441.364
1 week	0.122	0.973	4.313	138.773

Table B.86: Complete MSE results for XBT with 15 minutes granularity, segmented by model and learning period, 15-steps ahead prediction

ETH 15 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1/2 day	0.016	0.017	0.025	0.974
1 day	0.015	0.016	0.015	0.285
3 days	0.011	0.015	0.015	0.088
1 week	0.010	0.014	0.015	0.047

Table B.87: Complete MSE results for ETH with 15 minutes granularity, segmented by model and learning period, 1-step ahead prediction

ETH 15 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1/2 day	0.046	0.089	0.193	21.485
1 day	0.037	0.084	0.102	6.487
3 days	0.027	0.077	0.090	1.650
1 week	0.025	0.072	0.078	0.697

Table B.88: Complete MSE results for ETH with 15 minutes granularity, segmented by model and learning period, 3-steps ahead prediction

ETH 15 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1/2 day	0.078	0.226	0.962	143.158
1 day	0.060	0.213	0.393	39.686
3 days	0.044	0.193	0.277	9.686
1 week	0.040	0.174	0.212	3.666

Table B.89: Complete MSE results for ETH with 15 minutes granularity, segmented by model and learning period, 5-steps ahead prediction

ETH 15 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1/2 day	0.183	0.930	22.686	1,482.246
1 day	0.131	0.827	6.586	514.785
3 days	0.092	0.717	2.132	154.681
1 week	0.083	0.635	1.251	52.291

Table B.90: Complete MSE results for ETH with 15 minutes granularity, segmented by model and learning period, 10-steps ahead prediction

ETH 15 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1/2 day	0.383	2.250	184.146	2,752.942
1 day	0.270	1.938	52.934	1,490.029
3 days	0.189	1.634	11.701	742.907
1 week	0.170	1.432	5.621	292.861

Table B.91: Complete MSE results for ETH with 15 minutes granularity, segmented by model and learning period, 15-steps ahead prediction

LTC 15 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1/2 day	0.022	0.025	0.041	1.305
1 day	0.021	0.023	0.023	0.406
3 days	0.017	0.021	0.022	0.118
1 week	0.016	0.020	0.021	0.063

Table B.92: Complete MSE results for LTC with 15 minutes granularity, segmented by model and learning period, 1-step ahead prediction

LTC 15 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1/2 day	0.056	0.121	0.274	32.368
1 day	0.051	0.112	0.142	7.907
3 days	0.040	0.098	0.111	2.013
1 week	0.037	0.091	0.100	0.787

Table B.93: Complete MSE results for LTC with 15 minutes granularity, segmented by model and learning period, 3-steps ahead prediction

LTC 15 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1/2 day	0.096	0.296	1.359	202.937
1 day	0.079	0.272	0.576	46.450
3 days	0.062	0.236	0.319	11.132
1 week	0.057	0.212	0.265	3.819

Table B.94: Complete MSE results for LTC with 15 minutes granularity, segmented by model and learning period, 5-steps ahead prediction

LTC 15 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1/2 day	0.217	1.151	31.641	$1,777.481$
1 day	0.167	1.034	10.191	613.503
3 days	0.125	0.864	2.773	176.236
1 week	0.113	0.762	1.632	50.525

Table B.95: Complete MSE results for LTC with 15 minutes granularity, segmented by model and learning period, 10-steps ahead prediction

LTC 15 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1/2 day	0.411	2.821	240.648	12,568.240
1 day	0.339	2.420	81.081	1,751.751
3 days	0.250	1.948	16.483	874.762
1 week	0.224	1.696	7.338	282.663

Table B.96: Complete MSE results for LTC with 15 minutes granularity, segmented by model and learning period, 15-steps ahead prediction

XMR 15 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1/2 day	0.024	0.032	0.057	1.593
1 day	0.022	0.029	0.030	0.460
3 days	0.020	0.025	0.026	0.133
1 week	0.019	0.023	0.024	0.075

Table B.97: Complete MSE results for XMR with 15 minutes granularity, segmented by model and learning period, 1-step ahead prediction

XMR 15 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1/2 day	0.059	0.144	0.350	37.596
1 day	0.051	0.131	0.167	9.130
3 days	0.044	0.100	0.117	1.815
1 week	0.041	0.085	0.096	0.809

Table B.98: Complete MSE results for XMR with 15 minutes granularity, segmented by model and learning period, 3-steps ahead prediction

XMR 15 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1/2 day	0.101	0.356	1.627	230.418
1 day	0.078	0.320	0.607	53.618
3 days	0.068	0.232	0.325	9.439
1 week	0.065	0.189	0.240	3.629

Table B.99: Complete MSE results for XMR with 15 minutes granularity, segmented by model and learning period, 5-steps ahead prediction

XMR 15 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1/2 day	0.241	1.408	34.123	1,770.568
1 day	0.167	1.221	8.797	631.292
3 days	0.139	0.825	2.274	132.019
1 week	0.133	0.660	1.336	45.132

Table B.100: Complete MSE results for XMR with 15 minutes granularity, segmented by model and learning period, 10-steps ahead prediction

XMR 15 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1/2 day	0.503	3.454	258.083	6,488.461
1 day	0.363	2.885	67.839	1,660.005
3 days	0.295	1.911	11.838	603.731
1 week	0.275	1.494	5.677	232.917

Table B.101: Complete MSE results for XMR with 15 minutes granularity, segmented by model and learning period, 15-steps ahead prediction

XBT 30 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1 day	0.020	0.023	0.039	2.419
3 days	0.017	0.022	0.023	0.281
1 week	0.015	0.021	0.022	0.115
2 weeks	0.015	0.022	0.022	0.065

Table B.102: Complete MSE results for XBT with 30 minutes granularity, segmented by model and learning period, 1-step ahead prediction

XBT 30 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1 day	0.053	0.102	0.339	51.433
3 days	0.042	0.097	0.132	5.015
1 week	0.036	0.099	0.111	1.931
2 weeks	0.036	0.101	0.112	1.041

Table B.103: Complete MSE results for XBT with 30 minutes granularity, segmented by model and learning period, 3-steps ahead prediction

XBT 30 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1 day	0.092	0.235	1.851	285.469
3 days	0.068	0.220	0.460	30.115
1 week	0.059	0.221	0.319	10.382
2 weeks	0.059	0.225	0.291	5.727

Table B.104: Complete MSE results for XBT with 30 minutes granularity, segmented by model and learning period, 5-steps ahead prediction

XBT 30 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1 day	0.219	0.819	38.031	1,912.049
3 days	0.148	0.731	5.510	405.128
1 week	0.123	0.745	2.922	149.741
2 weeks	0.122	0.749	1.917	93.052

Table B.105: Complete MSE results for XBT with 30 minutes granularity, segmented by model and learning period, 10-steps ahead prediction

XBT 30 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1 day	0.475	1.975	252.521	12,058.055
3 days	0.318	1.657	38.457	1,499.480
1 week	0.272	1.649	18.621	789.679
2 weeks	0.274	1.669	10.000	557.708

Table B.106: Complete MSE results for XBT with 30 minutes granularity, segmented by model and learning period, 15-steps ahead prediction

ETH 30 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1 day	0.035	0.035	0.057	3.666
3 days	0.025	0.033	0.036	0.402
1 week	0.022	0.032	0.034	0.179
2 weeks	0.021	0.030	0.032	0.119

Table B.107: Complete MSE results for ETH with 30 minutes granularity, segmented by model and learning period, 1-step ahead prediction

ETH 30 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1 day	0.092	0.164	0.470	62.236
3 days	0.061	0.159	0.224	8.088
1 week	0.053	0.155	0.188	3.082
2 weeks	0.053	0.137	0.173	2.025

Table B.108: Complete MSE results for ETH with 30 minutes granularity, segmented by model and learning period, 3-steps ahead prediction

ETH 30 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1 day	0.155	0.387	2.424	366.266
3 days	0.097	0.370	0.757	48.638
1 week	0.084	0.365	0.563	16.780
2 weeks	0.082	0.312	0.479	10.847

Table B.109: Complete MSE results for ETH with 30 minutes granularity, segmented by model and learning period, 5-steps ahead prediction

ETH 30 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1 day	0.352	1.430	52.526	1,957.582
3 days	0.208	1.315	9.181	674.192
1 week	0.171	1.266	4.836	240.962
2 weeks	0.173	1.049	3.489	152.562

Table B.110: Complete MSE results for ETH with 30 minutes granularity, segmented by model and learning period, 10-steps ahead prediction

ETH 30 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1 day	0.712	3.471	358.987	15,284.718
3 days	0.428	2.974	64.924	1,842.462
1 week	0.361	2.815	29.427	1,162.509
2 weeks	0.363	2.340	19.231	794.030

Table B.111: Complete MSE results for ETH with 30 minutes granularity, segmented by model and learning period, 15-steps ahead prediction

LTC 30 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1 day	0.047	0.045	0.082	4.061
3 days	0.035	0.041	0.044	0.532
1 week	0.031	0.040	0.043	0.248
2 weeks	0.030	0.040	0.041	0.153

Table B.112: Complete MSE results for LTC with 30 minutes granularity, segmented by model and learning period, 1-step ahead prediction

LTC 30 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1 day	0.124	0.193	0.647	86.401
3 days	0.083	0.187	0.261	9.096
1 week	0.072	0.175	0.226	4.221
2 weeks	0.065	0.171	0.198	2.566

Table B.113: Complete MSE results for LTC with 30 minutes granularity, segmented by model and learning period, 3-steps ahead prediction

LTC 30 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1 day	0.205	0.440	3.330	515.899
3 days	0.126	0.423	0.936	55.642
1 week	0.110	0.393	0.649	23.934
2 weeks	0.100	0.377	0.527	14.464

Table B.114: Complete MSE results for LTC with 30 minutes granularity, segmented by model and learning period, 5-steps ahead prediction

LTC 30 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1 day	0.469	1.598	65.829	4,271.067
3 days	0.257	1.471	12.247	822.623
1 week	0.218	1.314	5.777	366.013
2 weeks	0.197	1.228	3.778	201.624

Table B.115: Complete MSE results for LTC with 30 minutes granularity, segmented by model and learning period, 10-steps ahead prediction

LTC 30 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1 day	0.881	3.790	400.535	165, 292.395
3 days	0.536	3.339	83.436	2, 672.071
1 week	0.473	2.900	36.046	1, 752.388
2 weeks	0.416	2.671	21.113	1, 119.694

Table B.116: Complete MSE results for LTC with 30 minutes granularity, segmented by model and learning period, 15-steps ahead prediction

XMR 30 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1 day	0.054	0.061	0.099	4.156
3 days	0.043	0.055	0.059	0.483
1 week	0.039	0.052	0.056	0.236
2 weeks	0.037	0.049	0.052	0.154

Table B.117: Complete MSE results for XMR with 30 minutes granularity, segmented by model and learning period, 1-step ahead prediction

XMR 30 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1 day	0.132	0.291	0.724	96.887
3 days	0.097	0.274	0.327	9.415
1 week	0.087	0.246	0.280	3.781
2 weeks	0.084	0.220	0.251	2.163

Table B.118: Complete MSE results for XMR with 30 minutes granularity, segmented by model and learning period, 3-steps ahead prediction

XMR 30 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1 day	0.221	0.717	3.587	572.788
3 days	0.153	0.680	1.110	55.857
1 week	0.133	0.590	0.838	20.857
2 weeks	0.129	0.521	0.719	11.075

Table B.119: Complete MSE results for XMR with 30 minutes granularity, segmented by model and learning period, 5-steps ahead prediction

XMR 30 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1 day	0.568	2.835	77.719	2,743.375
3 days	0.337	2.597	14.311	700.485
1 week	0.283	2.223	7.948	280.239
2 weeks	0.281	1.904	5.859	147.694

Table B.120: Complete MSE results for XMR with 30 minutes granularity, segmented by model and learning period, 10-steps ahead prediction

XMR 30 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1 day	1.204	6.822	479.420	84,744.159
3 days	0.702	5.871	103.061	1,812.873
1 week	0.605	5.003	49.048	1,167.359
2 weeks	0.603	4.220	34.111	753.181

Table B.121: Complete MSE results for XMR with 30 minutes granularity, segmented by model and learning period, 15-steps ahead prediction

XBT 1 hour	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 days	0.040	0.046	0.071	7.657
4 days	0.032	0.043	0.045	1.183
1 week	0.030	0.043	0.044	0.695
2 weeks	0.030	0.042	0.045	0.498

Table B.122: Complete MSE results for XBT with 1 hour granularity, segmented by model and learning period, 1-step ahead prediction

XBT 1 hour	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 days	0.107	0.204	0.677	137.034
4 days	0.081	0.195	0.344	23.508
1 week	0.075	0.195	0.297	15.328
2 weeks	0.075	0.201	0.270	10.292

Table B.123: Complete MSE results for XBT with 1 hour granularity, segmented by model and learning period, 3-steps ahead prediction

XBT 1 hour	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 days	0.175	0.461	3.982	746.075
4 days	0.126	0.434	1.670	132.186
1 week	0.115	0.436	1.358	83.971
2 weeks	0.117	0.452	1.113	57.358

Table B.124: Complete MSE results for XBT with 1 hour granularity, segmented by model and learning period, 5-steps ahead prediction

XBT 1 hour	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 days	0.430	1.640	83.591	9,342.936
4 days	0.306	1.494	36.096	1,527.274
1 week	0.278	1.462	25.511	1,136.993
2 weeks	0.267	1.503	21.262	929.240

Table B.125: Complete MSE results for XBT with 1 hour granularity, segmented by model and learning period, 10-steps ahead prediction

XBT 1 hour	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 days	0.920	3.867	418.245	437,664.347
4 days	0.698	3.534	230.784	7,750.111
1 week	0.641	3.358	169.742	6,615.728
2 weeks	0.629	3.462	144.905	6,200.822

Table B.126: Complete MSE results for XBT with 1 hour granularity, segmented by model and learning period, 15-steps ahead prediction

ETH 1 hour	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 days	0.076	0.070	0.112	6.708
4 days	0.056	0.066	0.073	1.636
1 week	0.047	0.063	0.069	1.058
2 weeks	0.047	0.061	0.063	0.844

Table B.127: Complete MSE results for ETH with 1 hour granularity, segmented by model and learning period, 1-step ahead prediction

ETH 1 hour	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 days	0.202	0.308	0.872	137.476
4 days	0.140	0.295	0.500	34.045
1 week	0.116	0.294	0.442	20.356
2 weeks	0.113	0.283	0.388	16.095

Table B.128: Complete MSE results for ETH with 1 hour granularity, segmented by model and learning period, 3-steps ahead prediction

ETH 1 hour	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 days	0.330	0.684	4.890	743.733
4 days	0.226	0.658	2.345	187.273
1 week	0.184	0.647	1.940	115.241
2 weeks	0.174	0.642	1.578	93.617

Table B.129: Complete MSE results for ETH with 1 hour granularity, segmented by model and learning period, 5-steps ahead prediction

ETH 1 hour	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 days	0.808	2.446	92.769	$18,665.684$
4 days	0.529	2.248	40.699	$1,739.018$
1 week	0.402	2.213	32.307	$1,628.106$
2 weeks	0.378	2.169	29.300	$1,759.729$

Table B.130: Complete MSE results for ETH with 1 hour granularity, segmented by model and learning period, 10-steps ahead prediction

ETH 1 hour	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 days	1.650	5.745	468.379	$1.561 * 10^6$
4 days	1.127	5.271	255.845	$6,254.076$
1 week	0.896	5.052	199.558	$12,174.116$
2 weeks	0.840	4.929	183.365	$20,618.023$

Table B.131: Complete MSE results for ETH with 1 hour granularity, segmented by model and learning period, 15-steps ahead prediction

LTC 1 hour	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 days	0.099	0.081	0.142	10.152
4 days	0.073	0.072	0.086	2.347
1 week	0.063	0.069	0.081	1.482
2 weeks	0.056	0.066	0.071	0.690

Table B.132: Complete MSE results for LTC with 1 hour granularity, segmented by model and learning period, 1-step ahead prediction

LTC 1 hour	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 days	0.277	0.302	1.110	229.090
4 days	0.182	0.254	0.536	44.696
1 week	0.146	0.243	0.427	24.767
2 weeks	0.130	0.228	0.327	11.072

Table B.133: Complete MSE results for LTC with 1 hour granularity, segmented by model and learning period, 3-steps ahead prediction

LTC 1 hour	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 days	0.466	0.621	6.234	1,201.421
4 days	0.310	0.529	2.555	238.843
1 week	0.232	0.480	1.700	117.824
2 weeks	0.197	0.462	1.064	57.051

Table B.134: Complete MSE results for LTC with 1 hour granularity, segmented by model and learning period, 5-steps ahead prediction

LTC 1 hour	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 days	1.058	2.005	116.594	43,733.155
4 days	0.663	1.542	41.621	1,986.798
1 week	0.498	1.431	24.085	1,229.977
2 weeks	0.426	1.379	13.724	687.359

Table B.135: Complete MSE results for LTC with 1 hour granularity, segmented by model and learning period, 10-steps ahead prediction

LTC 1 hour	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 days	2.068	4.472	514.943	$9.776 * 10^6$
4 days	1.459	3.519	250.325	$14,266.621$
1 week	1.163	3.159	148.903	$5,043.688$
2 weeks	0.947	3.051	88.864	$2,847.507$

Table B.136: Complete MSE results for LTC with 1 hour granularity, segmented by model and learning period, 15-steps ahead prediction

XMR 1 hour	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 days	0.124	0.110	0.186	11.516
4 days	0.100	0.105	0.116	2.010
1 week	0.080	0.101	0.110	1.271
2 weeks	0.077	0.094	0.104	0.749

Table B.137: Complete MSE results for XMR with 1 hour granularity, segmented by model and learning period, 1-step ahead prediction

XMR 1 hour	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 days	0.337	0.506	1.479	225.745
4 days	0.240	0.509	0.801	45.653
1 week	0.181	0.485	0.717	29.305
2 weeks	0.175	0.415	0.624	16.165

Table B.138: Complete MSE results for XMR with 1 hour granularity, segmented by model and learning period, 3-steps ahead prediction

XMR 1 hour	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 days	0.590	1.241	8.111	$1,363.969$
4 days	0.399	1.251	4.043	278.751
1 week	0.298	1.186	3.282	185.989
2 weeks	0.275	0.967	2.644	101.874

Table B.139: Complete MSE results for XMR with 1 hour granularity, segmented by model and learning period, 5-steps ahead prediction

XMR 1 hour	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 days	1.506	4.597	159.248	$102,664.811$
4 days	0.888	4.500	80.140	$5,609.081$
1 week	0.668	4.088	62.995	$4,375.965$
2 weeks	0.616	3.350	51.782	$2,433.813$

Table B.140: Complete MSE results for XMR with 1 hour granularity, segmented by model and learning period, 10-steps ahead prediction

XMR 1 hour	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 days	3.063	11.058	615.822	$36.079 * 10^6$
4 days	1.886	10.324	400.960	$146,083.759$
1 week	1.514	9.440	332.390	$101,291.327$
2 weeks	1.328	7.541	275.865	$40,412.627$

Table B.141: Complete MSE results for XMR with 1 hour granularity, segmented by model and learning period, 15-steps ahead prediction

XBT 1 day	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 weeks	1.636	2.171	4.267	$1,435.962$
3 weeks	1.116	4.467	5.217	818.033
4 weeks	1.178	51.104	7.018	$1,061.999$
6 weeks	1.049	1.609	10.786	428.841

Table B.142: Complete MSE results for XBT with 1 day granularity, segmented by model and learning period, 1-step ahead prediction

XBT 1 day	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 weeks	7.978	13.399	49.095	$368,258.826$
3 weeks	3.557	16.673	56.366	$79,817.109$
4 weeks	3.651	337.300	116.825	$35,731.998$
6 weeks	4.308	11.189	118.182	$37,162.108$

Table B.143: Complete MSE results for XBT with 1 day granularity, segmented by model and learning period, 3-steps ahead prediction

XBT 1 day	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 weeks	17.161	39.447	296.359	$8.732 * 10^9$
3 weeks	8.500	33.593	306.359	$12.451 * 10^6$
4 weeks	8.089	$1,667.374$	425.940	$11.594 * 10^6$
6 weeks	7.724	29.328	565.079	$2.703 * 10^6$

Table B.144: Complete MSE results for XBT with 1 day granularity, segmented by model and learning period, 5-steps ahead prediction

XBT 1 day	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 weeks	55.883	192.062	$1,825.263$	$2.384 * 10^{18}$
3 weeks	26.359	130.931	$1,323.582$	$291.215 * 10^{12}$
4 weeks	33.049	$428,308.185$	$1,712.581$	$2,302 * 10^{15}$
6 weeks	26.272	107.654	$2,888.262$	$317.057 * 10^{12}$

Table B.145: Complete MSE results for XBT with 1 day granularity, segmented by model and learning period, 10-steps ahead prediction

XBT 1 day	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 weeks	116.985	531.958	$2,882.087$	$23.730 * 10^{33}$
3 weeks	70.602	370.028	$2,242.020$	$18.240 * 10^{24}$
4 weeks	100.828	$4.949 * 10^{15}$	$2,913.518$	$6.169 * 10^{27}$
6 weeks	76.965	270.054	$183,999.721$	$3.793 * 10^{24}$

Table B.146: Complete MSE results for XBT with 1 day granularity, segmented by model and learning period, 15-steps ahead prediction

ETH 1 day	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 weeks	3.165	3.489	5.376	$2,068.246$
3 weeks	2.623	6.027	7.878	206.962
4 weeks	2.300	63.734	9.716	841.439
6 weeks	2.569	2.759	23.182	667.880

Table B.147: Complete MSE results for ETH with 1 day granularity, segmented by model and learning period, 1-step ahead prediction

ETH 1 day	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 weeks	11.944	17.955	48.036	$57,073.550$
3 weeks	6.964	20.864	52.077	$1,954.356$
4 weeks	6.234	422.676	121.013	$11,177.972$
6 weeks	7.697	14.001	145.026	$50,001.977$

Table B.148: Complete MSE results for ETH with 1 day granularity, segmented by model and learning period, 3-steps ahead prediction

ETH 1 day	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 weeks	30.257	51.965	312.503	$18.323 * 10^6$
3 weeks	15.156	48.256	319.252	$3,302.030$
4 weeks	13.399	$1,840.275$	469.540	$820,590.771$
6 weeks	16.121	37.029	591.408	$10.209 * 10^6$

Table B.149: Complete MSE results for ETH with 1 day granularity, segmented by model and learning period, 5-steps ahead prediction

ETH 1 day	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 weeks	118.980	222.580	$1,630.320$	$13.565 * 10^{18}$
3 weeks	47.789	190.262	$1,229.182$	$683.000 * 10^6$
4 weeks	53.511	$69.519 * 10^6$	$1,672.610$	$2.256 * 10^{12}$
6 weeks	61.199	125.427	$2,333.296$	$30.411 * 10^{15}$

Table B.150: Complete MSE results for ETH with 1 day granularity, segmented by model and learning period, 10-steps ahead prediction

ETH 1 day	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 weeks	267.574	580.811	$3,467.906$	$330.470 * 10^{30}$
3 weeks	125.611	412.142	$1,852.539$	$2.255 * 10^{15}$
4 weeks	180.747	$54.855 * 10^{24}$	$13,185.570$	$52.802 * 10^{18}$
6 weeks	173.049	326.312	$11,308.939$	$112.315 * 10^{33}$

Table B.151: Complete MSE results for ETH with 1 day granularity, segmented by model and learning period, 15-steps ahead prediction

LTC 1 day	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 weeks	4.784	3.486	4.548	$2,058.873$
3 weeks	3.592	5.988	8.061	231.272
4 weeks	2.229	70.894	14.526	396.517
6 weeks	2.433	2.922	17.639	378.535

Table B.152: Complete MSE results for LTC with 1 day granularity, segmented by model and learning period, 1-step ahead prediction

LTC 1 day	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 weeks	17.720	17.491	64.109	$20,954.836$
3 weeks	12.153	23.263	63.831	$1,702.268$
4 weeks	8.940	$1,133.281$	106.768	$16,680.927$
6 weeks	7.947	14.759	148.250	$30,293.543$

Table B.153: Complete MSE results for LTC with 1 day granularity, segmented by model and learning period, 3-steps ahead prediction

LTC 1 day	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 weeks	35.393	48.565	345.154	$6.292 * 10^9$
3 weeks	24.070	41.212	311.990	$6,942.175$
4 weeks	18.827	$6,283.889$	472.348	$1.375 * 10^6$
6 weeks	17.853	36.981	583.947	$5.934 * 10^6$

Table B.154: Complete MSE results for LTC with 1 day granularity, segmented by model and learning period, 5-steps ahead prediction

LTC 1 day	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 weeks	93.612	228.804	$1,083.953$	$69.723 * 10^{21}$
3 weeks	50.362	155.605	$1,162.554$	$7.767 * 10^6$
4 weeks	38.038	$2.692 * 10^{12}$	$1,671.753$	$1.988 * 10^{12}$
6 weeks	72.695	139.656	$2,565.069$	$79.993 * 10^{12}$

Table B.155: Complete MSE results for LTC with 1 day granularity, segmented by model and learning period, 10-steps ahead prediction

LTC 1 day	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 weeks	255.285	578.819	1,820.365	$91.930 * 10^{30}$
3 weeks	178.551	400.842	1,927.831	$89,231 * 10^{12}$
4 weeks	167.162	$282.283 * 10^{27}$	3,072.647	$11.646 * 10^{21}$
6 weeks	238.285	355.566	133,836.150	$138.656 * 10^{18}$

Table B.156: Complete MSE results for LTC with 1 day granularity, segmented by model and learning period, 15-steps ahead prediction

XMR 1 day	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 weeks	4.316	4.578	4.827	1,798.490
3 weeks	2.227	6.385	9.043	563.623
4 weeks	2.946	84.736	15.405	1,176.480
6 weeks	2.322	2.660	19.261	440.439

Table B.157: Complete MSE results for XMR with 1 day granularity, segmented by model and learning period, 1-step ahead prediction

XMR 1 day	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 weeks	22.661	21.691	55.241	353,299.549
3 weeks	10.059	20.194	77.600	76,530.111
4 weeks	10.753	596.116	120.562	45,433.286
6 weeks	7.891	15.461	160.680	68,413.119

Table B.158: Complete MSE results for XMR with 1 day granularity, segmented by model and learning period, 3-steps ahead prediction

XMR 1 day	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 weeks	42.933	49.750	332.612	$535.377 * 10^{6}$
3 weeks	23.011	42.892	428.815	$7.625 * 10^{6}$
4 weeks	19.769	1,971.555	511.482	$21.011 * 10^{6}$
6 weeks	17.882	35.375	632.025	$9.610 * 10^{6}$

Table B.159: Complete MSE results for XMR with 1 day granularity, segmented by model and learning period, 5-steps ahead prediction

XMR 1 day	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 weeks	182.762	209.814	$1,813.393$	$138.178 * 10^{18}$
3 weeks	81.314	185.670	$1,554.021$	$126.894 * 10^{12}$
4 weeks	56.217	$10.533 * 10^{6}$	$1,814.391$	$56.821 * 10^{15}$
6 weeks	70.749	121.294	$2,998.765$	$72.459 * 10^{12}$

Table B.160: Complete MSE results for XMR with 1 day granularity, segmented by model and learning period, 10-steps ahead prediction

XMR 1 day	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 weeks	346.598	581.506	$3,617.814$	$297.183 * 10^{30}$
3 weeks	198.472	417.552	$3,009.989$	$161.620 * 10^{21}$
4 weeks	212.974	$36.314 * 10^{18}$	$4,702.705$	$76.929 * 10^{27}$
6 weeks	177.028	285.929	$67,068.687$	$129.825 * 10^{15}$

Table B.161: Complete MSE results for XMR with 1 day granularity, segmented by model and learning period, 15-steps ahead prediction

XBT 15 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1/2 day	0.426	0.996	0.316	0.024
1 day	0.628	0.996	0.527	0.242
3 days	0.910	0.992	0.797	0.666
1 week	0.949	0.981	0.877	0.830

Table B.162: Complete share of predictions for XBT with 15 minutes granularity, segmented by model and learning period

ETH 15 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1/2 day	0.403	0.997	0.320	0.024
1 day	0.575	0.997	0.531	0.244
3 days	0.901	0.992	0.797	0.666
1 week	0.975	0.981	0.877	0.830

Table B.163: Complete share of predictions for ETH with 15 minutes granularity, segmented by model and learning period

LTC 15 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1/2 day	0.335	0.994	0.316	0.024
1 day	0.472	0.994	0.528	0.239
3 days	0.760	0.992	0.797	0.666
1 week	0.874	0.981	0.878	0.830

Table B.164: Complete share of predictions for LTC with 15 minutes granularity, segmented by model and learning period

XMR 15 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1/2 day	0.369	0.995	0.317	0.024
1 day	0.488	0.995	0.527	0.241
3 days	0.731	0.992	0.797	0.666
1 week	0.833	0.981	0.877	0.829

Table B.165: Complete share of predictions for XMR with 15 minutes granularity, segmented by model and learning period

XBT 30 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1 day	0.449	0.995	0.461	0.055
3 days	0.834	0.992	0.774	0.637
1 week	0.953	0.981	0.868	0.821
2 weeks	0.958	0.962	0.917	0.893

Table B.166: Complete share of predictions for XBT with 30 minutes granularity, segmented by model and learning period

ETH 30 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1 day	0.420	0.997	0.463	0.056
3 days	0.788	0.992	0.776	0.637
1 week	0.960	0.981	0.868	0.820
2 weeks	0.962	0.962	0.917	0.892

Table B.167: Complete share of predictions for ETH with 30 minutes granularity, segmented by model and learning period

LTC 30 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1 day	0.335	0.994	0.459	0.057
3 days	0.613	0.992	0.775	0.638
1 week	0.831	0.981	0.868	0.821
2 weeks	0.910	0.962	0.917	0.892

Table B.168: Complete share of predictions for LTC with 30 minutes granularity, segmented by model and learning period

XMR 30 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1 day	0.352	0.994	0.459	0.056
3 days	0.584	0.992	0.775	0.638
1 week	0.769	0.981	0.868	0.821
2 weeks	0.822	0.962	0.917	0.893

Table B.169: Complete share of predictions for XMR with 30 minutes granularity, segmented by model and learning period

XBT 1 hour	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 days	0.457	0.995	0.643	0.075
4 days	0.682	0.989	0.799	0.680
1 week	0.873	0.981	0.861	0.808
2 weeks	0.952	0.962	0.915	0.888

Table B.170: Complete share of predictions for XBT with 1 hour granularity, segmented by model and learning period

ETH 1 hour	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 days	0.383	0.995	0.645	0.074
4 days	0.583	0.989	0.800	0.679
1 week	0.774	0.981	0.862	0.806
2 weeks	0.892	0.962	0.916	0.888

Table B.171: Complete share of predictions for ETH with 1 hour granularity, segmented by model and learning period

LTC 1 hour	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 days	0.297	0.994	0.645	0.077
4 days	0.446	0.989	0.799	0.682
1 week	0.662	0.981	0.862	0.806
2 weeks	0.879	0.962	0.915	0.888

Table B.172: Complete share of predictions for LTC with 1 hour granularity, segmented by model and learning period

XMR 1 hour	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 days	0.317	0.994	0.649	0.076
4 days	0.480	0.989	0.800	0.681
1 week	0.692	0.981	0.864	0.806
2 weeks	0.816	0.962	0.916	0.884

Table B.173: Complete share of predictions for XMR with 1 hour granularity, segmented by model and learning period

XBT 1 day	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 weeks	0.320	0.962	0.426	0.071
3 weeks	0.385	0.943	0.587	0.109
4 weeks	0.454	0.888	0.669	0.180
6 weeks	0.481	0.885	0.746	0.128

Table B.174: Complete share of predictions for XBT with 1 day granularity, segmented by model and learning period

ETH 1 day	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 weeks	0.276	0.962	0.426	0.071
3 weeks	0.292	0.943	0.571	0.104
4 weeks	0.339	0.885	0.664	0.180
6 weeks	0.402	0.885	0.724	0.178

Table B.175: Complete share of predictions for ETH with 1 day granularity, segmented by model and learning period

LTC 1 day	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 weeks	0.213	0.962	0.432	0.060
3 weeks	0.251	0.943	0.582	0.107
4 weeks	0.292	0.880	0.678	0.158
6 weeks	0.361	0.885	0.721	0.148

Table B.176: Complete share of predictions for LTC with 1 day granularity, segmented by model and learning period

XMR 1 day	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 weeks	0.249	0.962	0.429	0.066
3 weeks	0.325	0.943	0.568	0.104
4 weeks	0.369	0.883	0.667	0.161
6 weeks	0.380	0.885	0.699	0.137

Table B.177: Complete share of predictions for XMR with 1 day granularity, segmented by model and learning period

XBT 15 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1/2 day	21.206	311.563	5.245	1.319
1 day	893.448	366.015	53.004	1.364
3 days	26,151.749	4,680.705	737.770	10.318
1 week	40,241.414	5,277.847	2,742.127	74.544

Table B.178: Complete returns with 0.00% fees for XBT with 15 minutes granularity, segmented by model and learning period

ETH 15 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1/2 day	103.465	717.314	4.992	0.726
1 day	2,989.643	38,018.119	103.558	2.682
3 days	62,707.431	72,786.174	6,516.292	11.991
1 week	923,093.846	63,201.633	17,106.529	117.895

Table B.179: Complete returns with 0.00% fees for ETH with 15 minutes granularity, segmented by model and learning period

LTC 15 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1/2 day	57.274	288.193	4.892	1.347
1 day	246.494	301.696	30.060	3.885
3 days	6,192.644	3,424.498	251.276	24.897
1 week	17,879.484	1,854.213	472.234	70.204

Table B.180: Complete returns with 0.00% fees for LTC with 15 minutes granularity, segmented by model and learning period

XMR 15 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1/2 day	7.492	40.903	7.417	0.977
1 day	311.612	44.213	28.447	1.162
3 days	774.503	354.288	49.915	6.020
1 week	6,075.430	186.316	69.931	30.795

Table B.181: Complete returns with 0.00% fees for XMR with 15 minutes granularity, segmented by model and learning period

XBT 30 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1 day	9.833	48.370	3.613	0.912
3 days	383.482	238.902	96.777	6.756
1 week	2,260.665	254.167	274.751	14.958
2 weeks	2,803.823	465.216	332.107	25.785

Table B.182: Complete returns with 0.00% fees for XBT with 30 minutes granularity, segmented by model and learning period

ETH 30 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1 day	28.212	766.847	5.682	2.431
3 days	644.836	484.091	167.923	6.129
1 week	13,028.146	977.874	683.308	17.394
2 weeks	16,653.559	1,552.875	1,543.981	39.467

Table B.183: Complete returns with 0.00% fees for ETH with 30 minutes granularity, segmented by model and learning period

LTC 30 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1 day	17.088	56.636	3.433	4.412
3 days	274.941	254.767	31.938	3.927
1 week	2,281.637	433.525	583.483	26.114
2 weeks	1,590.976	142.852	875.266	14.941

Table B.184: Complete returns with 0.00% fees for LTC with 30 minutes granularity, segmented by model and learning period

XMR 30 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1 day	3.916	29.028	3.125	5.077
3 days	74.694	211.802	63.236	9.718
1 week	773.400	183.681	142.931	104.107
2 weeks	1,526.767	416.362	239.637	25.954

Table B.185: Complete returns with 0.00% fees for XMR with 30 minutes granularity, segmented by model and learning period

XBT 1 hour	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 days	12.212	38.954	3.255	0.935
4 days	11.108	38.521	20.183	1.028
1 week	53.409	56.428	37.480	2.625
2 weeks	139.777	60.759	47.975	5.742

Table B.186: Complete returns with 0.00% fees for XBT with 1 hour granularity, segmented by model and learning period

ETH 1 hour	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 days	4.379	17.527	4.015	2.917
4 days	16.095	40.195	20.813	6.044
1 week	93.033	37.866	51.175	6.252
2 weeks	85.862	50.873	90.420	2.090

Table B.187: Complete returns with 0.00% fees for ETH with 1 hour granularity, segmented by model and learning period

LTC 1 hour	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 days	5.932	2.661	3.128	3.257
4 days	9.818	24.993	16.136	3.986
1 week	27.642	16.787	19.279	2.934
2 weeks	117.998	13.406	34.829	2.411

Table B.188: Complete returns with 0.00% fees for LTC with 1 hour granularity, segmented by model and learning period

XMR 1 hour	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 days	6.291	27.198	10.583	0.727
4 days	17.713	57.238	39.405	4.775
1 week	67.764	51.273	126.892	5.190
2 weeks	106.284	72.495	196.495	2.354

Table B.189: Complete returns with 0.00% fees for XMR with 1 hour granularity, segmented by model and learning period

XBT 1 day	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 weeks	3.014	6.350	2.432	0.602
3 weeks	2.047	2.181	2.158	0.847
4 weeks	1.367	1.958	0.981	2.361
6 weeks	1.305	3.650	1.378	0.877

Table B.190: Complete returns with 0.00% fees for XBT with 1 day granularity, segmented by model and learning period

ETH 1 day	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 weeks	1.650	1.218	0.999	4.005
3 weeks	2.556	1.093	2.889	2.386
4 weeks	2.132	1.622	2.851	0.587
6 weeks	1.442	2.182	0.353	1.839

Table B.191: Complete returns with 0.00% fees for ETH with 1 day granularity, segmented by model and learning period

LTC 1 day	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 weeks	2.259	2.546	4.451	6.581
3 weeks	1.755	1.772	0.749	3.362
4 weeks	1.502	0.478	1.232	2.141
6 weeks	3.276	1.536	1.177	0.994

Table B.192: Complete returns with 0.00% fees for LTC with 1 day granularity, segmented by model and learning period

XMR 1 day	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 weeks	1.484	1.413	2.460	5.872
3 weeks	2.288	2.208	8.403	5.795
4 weeks	1.767	1.286	1.725	6.462
6 weeks	1.698	1.158	3.115	1.232

Table B.193: Complete returns with 0.00% fees for XMR with 1 day granularity, segmented by model and learning period

XBT 15 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1/2 day	0.000	0.000	0.000	0.721
1 day	0.000	0.000	0.000	0.031
3 days	0.000	0.000	0.000	0.001
1 week	0.000	0.000	0.000	0.000

Table B.194: Complete returns with 0.26% fees for XBT with 15 minutes granularity, segmented by model and learning period

ETH 15 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1/2 day	0.000	0.000	0.000	0.401
1 day	0.000	0.000	0.000	0.070
3 days	0.000	0.000	0.000	0.001
1 week	0.000	0.000	0.000	0.001

Table B.195: Complete returns with 0.26% fees for ETH with 15 minutes granularity, segmented by model and learning period

LTC 15 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1/2 day	0.000	0.000	0.000	0.776
1 day	0.000	0.000	0.000	0.116
3 days	0.000	0.000	0.000	0.002
1 week	0.000	0.000	0.000	0.000

Table B.196: Complete returns with 0.26% fees for LTC with 15 minutes granularity, segmented by model and learning period

XMR 15 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1/2 day	0.000	0.000	0.000	0.566
1 day	0.000	0.000	0.000	0.026
3 days	0.000	0.000	0.000	0.001
1 week	0.000	0.000	0.000	0.000

Table B.197: Complete returns with 0.26% fees for XMR with 15 minutes granularity, segmented by model and learning period

XBT 30 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1 day	0.003	0.002	0.000	0.466
3 days	0.000	0.000	0.000	0.145
1 week	0.000	0.000	0.000	0.058
2 weeks	0.000	0.000	0.000	0.047

Table B.198: Complete returns with 0.26% fees for XBT with 30 minutes granularity, segmented by model and learning period

ETH 30 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1 day	0.010	0.000	0.001	1.197
3 days	0.000	0.000	0.000	0.126
1 week	0.000	0.000	0.000	0.088
2 weeks	0.000	0.000	0.000	0.062

Table B.199: Complete returns with 0.26% fees for ETH with 30 minutes granularity, segmented by model and learning period

LTC 30 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1 day	0.045	0.001	0.000	2.219
3 days	0.000	0.000	0.000	0.084
1 week	0.000	0.000	0.000	0.179
2 weeks	0.000	0.000	0.000	0.049

Table B.200: Complete returns with 0.26% fees for LTC with 30 minutes granularity, segmented by model and learning period

XMR 30 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1 day	0.010	0.001	0.000	2.514
3 days	0.000	0.000	0.000	0.232
1 week	0.000	0.000	0.000	0.447
2 weeks	0.000	0.000	0.000	0.057

Table B.201: Complete returns with 0.26% fees for XMR with 30 minutes granularity, segmented by model and learning period

XBT 1 hour	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 days	0.211	0.005	0.007	0.558
4 days	0.006	0.006	0.021	0.199
1 week	0.002	0.011	0.025	0.459
2 weeks	0.001	0.019	0.026	0.900

Table B.202: Complete returns with 0.26% fees for XBT with 1 hour granularity, segmented by model and learning period

ETH 1 hour	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 days	0.177	0.002	0.006	1.816
4 days	0.029	0.006	0.018	1.079
1 week	0.013	0.007	0.027	0.915
2 weeks	0.002	0.015	0.041	0.282

Table B.203: Complete returns with 0.26% fees for ETH with 1 hour granularity, segmented by model and learning period

LTC 1 hour	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 days	0.495	0.011	0.005	1.955
4 days	0.095	0.002	0.015	0.661
1 week	0.012	0.001	0.009	0.537
2 weeks	0.002	0.001	0.010	0.402

Table B.204: Complete returns with 0.26% fees for LTC with 1 hour granularity, segmented by model and learning period

XMR 1 hour	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 days	0.498	0.173	0.014	0.462
4 days	0.137	0.013	0.038	0.830
1 week	0.030	0.014	0.078	1.077
2 weeks	0.006	0.032	0.129	0.350

Table B.205: Complete returns with 0.26% fees for XMR with 1 hour granularity, segmented by model and learning period

XBT 1 day	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 weeks	2.906	4.503	2.135	0.593
3 weeks	1.923	1.438	1.707	0.834
4 weeks	1.219	1.291	0.707	2.253
6 weeks	1.134	2.713	0.992	0.859

Table B.206: Complete returns with 0.26% fees for XBT with 1 day granularity, segmented by model and learning period

ETH 1 day	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 weeks	1.582	0.820	0.855	3.923
3 weeks	2.439	0.771	2.274	2.313
4 weeks	2.034	1.098	2.141	0.554
6 weeks	1.383	1.540	0.262	1.746

Table B.207: Complete returns with 0.26% fees for ETH with 1 day granularity, segmented by model and learning period

LTC 1 day	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 weeks	2.167	1.714	3.691	6.479
3 weeks	1.674	1.174	0.580	3.225
4 weeks	1.434	0.306	0.930	2.043
6 weeks	3.062	1.089	0.826	0.944

Table B.208: Complete returns with 0.26% fees for LTC with 1 day granularity, segmented by model and learning period

XMR 1 day	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 weeks	1.423	0.961	2.148	5.721
3 weeks	2.218	1.518	6.683	5.646
4 weeks	1.686	0.826	1.269	6.134
6 weeks	1.663	0.852	2.255	1.170

Table B.209: Complete returns with 0.26% fees for XMR with 1 day granularity, segmented by model and learning period

XBT 15 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1/2 day	0.044	0.150	0.044	1.046
1 day	0.038	0.245	0.043	0.317
3 days	0.004	0.017	0.034	0.296
1 week	0.003	0.028	0.069	0.404

Table B.210: Complete returns with 0.10% fees for XBT with 15 minutes granularity, segmented by model and learning period

ETH 15 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1/2 day	0.421	0.298	0.034	0.578
1 day	0.411	0.105	0.078	0.662
3 days	0.013	0.391	0.335	0.366
1 week	0.079	0.566	0.532	1.068

Table B.211: Complete returns with 0.10% fees for ETH with 15 minutes granularity, segmented by model and learning period

LTC 15 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1/2 day	0.573	0.095	0.034	1.090
1 day	0.191	0.158	0.022	1.009
3 days	0.021	0.020	0.011	0.659
1 week	0.007	0.019	0.013	0.542

Table B.212: Complete returns with 0.10% fees for LTC with 15 minutes granularity, segmented by model and learning period

XMR 15 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1/2 day	0.062	0.010	0.046	0.792
1 day	0.312	0.023	0.019	0.268
3 days	0.007	0.004	0.003	0.190
1 week	0.011	0.005	0.004	0.402

Table B.213: Complete returns with 0.10% fees for XMR with 15 minutes granularity, segmented by model and learning period

XBT 30 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1 day	0.432	0.983	0.110	0.705
3 days	0.237	0.261	0.563	1.543
1 week	0.386	0.364	0.867	1.772
2 weeks	0.443	0.794	0.837	2.285

Table B.214: Complete returns with 0.10% fees for XBT with 30 minutes granularity, segmented by model and learning period

ETH 30 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1 day	1.350	0.636	0.161	1.852
3 days	0.517	0.572	1.005	1.377
1 week	1.717	1.519	2.402	2.282
2 weeks	1.804	3.224	4.175	3.294

Table B.215: Complete returns with 0.10% fees for ETH with 30 minutes granularity, segmented by model and learning period

LTC 30 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1 day	1.742	0.956	0.092	3.388
3 days	1.377	0.319	0.168	0.897
1 week	1.089	0.574	2.030	3.848
2 weeks	0.288	0.225	2.013	1.660

Table B.216: Complete returns with 0.10% fees for LTC with 30 minutes granularity, segmented by model and learning period

XMR 30 minutes	Univariate	SVI not differenced	SVI binary	SVI quartiles
1 day	0.389	0.487	0.087	3.875
3 days	0.588	0.309	0.361	2.315
1 week	0.886	0.441	0.507	12.812
2 weeks	1.034	1.356	0.836	2.467

Table B.217: Complete returns with 0.10% fees for XMR with 30 minutes granularity, segmented by model and learning period

XBT 1 hour	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 days	2.569	1.235	0.313	0.767
4 days	0.607	1.312	1.444	0.547
1 week	1.037	2.120	2.244	1.343
2 weeks	1.635	2.733	2.657	2.817

Table B.218: Complete returns with 0.10% fees for XBT with 1 hour granularity, segmented by model and learning period

ETH 1 hour	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 days	1.277	0.484	0.333	2.431
4 days	1.424	1.331	1.372	3.116
1 week	3.069	1.358	2.823	2.988
2 weeks	1.293	2.234	4.707	0.967

Table B.219: Complete returns with 0.10% fees for ETH with 1 hour granularity, segmented by model and learning period

LTC 1 hour	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 days	2.284	0.319	0.261	2.677
4 days	1.654	0.684	1.107	1.998
1 week	1.427	0.465	1.016	1.528
2 weeks	1.734	0.403	1.542	1.211

Table B.220: Complete returns with 0.10% fees for LTC with 1 hour granularity, segmented by model and learning period

XMR 1 hour	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 days	2.374	3.897	0.839	0.611
4 days	2.733	2.306	2.725	2.438
1 week	3.492	2.207	7.418	2.836
2 weeks	2.540	3.706	11.766	1.132

Table B.221: Complete returns with 0.10% fees for XMR with 1 hour granularity, segmented by model and learning period

XBT 1 day	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 weeks	2.972	5.564	2.313	0.598
3 weeks	1.998	1.859	1.972	0.842
4 weeks	1.308	1.668	0.865	2.319
6 weeks	1.237	3.257	1.214	0.870

Table B.222: Complete returns with 0.10% fees for XBT with 1 day granularity, segmented by model and learning period

ETH 1 day	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 weeks	1.623	1.046	0.941	3.973
3 weeks	2.510	0.956	2.635	2.358
4 weeks	2.094	1.396	2.554	0.574
6 weeks	1.419	1.909	0.315	1.802

Table B.223: Complete returns with 0.10% fees for ETH with 1 day granularity, segmented by model and learning period

LTC 1 day	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 weeks	2.223	2.186	4.142	6.542
3 weeks	1.723	1.512	0.679	3.309
4 weeks	1.476	0.402	1.106	2.103
6 weeks	3.192	1.346	1.027	0.974

Table B.224: Complete returns with 0.10% fees for LTC with 1 day granularity, segmented by model and learning period

XMR 1 day	Univariate	SVI not differenced	SVI binary	SVI quartiles
2 weeks	1.460	1.219	2.335	5.814
3 weeks	2.261	1.912	7.695	5.737
4 weeks	1.736	1.085	1.533	6.334
6 weeks	1.684	1.029	2.751	1.208

Table B.225: Complete returns with 0.10% fees for XMR with 1 day granularity, segmented by model and learning period

Declaration of Authorship

I hereby confirm that I have authored this Master's thesis independently and without use of others than the indicated sources. All passages which are literally or in general matter taken out of publications or other sources are marked as such.

Prague, 4^{th} February, 2019

Vojtěch Pulec